WATER URBANISM: BUILDING MORE COHERENT CITIES

by

HOPE HUI RISING

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Student: Hope Hui Rising

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This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Landscape Architecture by:

Robert Ribe	Chairperson
Amy Lobben	Core Member
Deni Ruggeri	Core Member
Elliot Berkman	Institutional Representative

and

Scott L. Pratt	Dean of the Graduate School

Original approval signatures are on file with the University of Oregon Graduate School.

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DISSERTATION ABSTRACT

Hope Hui Rising

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A more water-coherent approach is postulated as a primary pathway through which biophilic urbanism contributes to livability and climate change adaptation. Previous studies have shown that upstream water retention is more cost-effective than downstream for mitigating flood risks downstream. This dissertation proposes a research design for generating an iconography of water urbanism to make upstream cities more coherent. I tested a hypothesis of aquaphilic urbanism as a water-based sense of place that evokes water-based place attachment to help adapt cities and individuals to water-coherent urbanism.

Cognitive mapping, photovoice, and emotional recall protocols were conducted during semi-structured interviews with 60 residents and visitors sampled from eight water-centric cities in the Netherlands, Germany, and Belgium. The participants provided 55 sketch maps. I performed content analyses, regression analyses, path analyses, and mediation analyses to study the relationships of 1) pictorial aquaphilia (intrinsic attachment to safe and clean water scenes) and waterscape imageability, 2) waterscape imageability and the coherence of city image, 3) egocentric aquaphilia (attachment to water-based spatial anchors) and allocentric aquaphilia (attachment to water-centric cities), and 4) the coherence of city image, allocentric aquaphilia, and openness towards water-coherent urbanism.

Content analyses show that waterscape imageability and pictorial aquaphilia were the two most common reasons why participants mentioned the five waterscape types, including water landmarks, canals, lakes, rivers, and harbors, during the three recall protocols. Regression analyses indicate that water is a sixth element of imageability and that the imageable structure of canals and rivers and the identifiability of water landmarks significantly influenced the aesthetic coherence of city image. Path analyses suggest that allocentric aquaphilia can be attributed to water-based familiarity, water-based place identity (or identifiability), water-based comfort, and water-based place dependence (or orientation) evoked by water-based spatial anchors. Mediation analyses reveal that water-based goal affordance (as a construct of water-based comfort and water-based place dependence) aided environmental adaptation, while water-based imageability (as a construct of water-based familiarity and water-based place identity) helped adapt cities and individuals to water-coherent urbanism. Canal mappability mediated the effects of gender and of visitor versus resident on the coherence of city image to facilitate environmental adaptation.

CURRICULUM VITAE

NAME OF AUTHOR: Hope Hui Rising

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene
University of Michigan, Ann Arbor
National Taiwan University, Taipei

DEGREES AWARDED:

Doctor of Philosophy in Landscape Architecture, 2015, University of Oregon
Master of Landscape Architecture, 2000, University of Michigan
Master of Urban Planning, 2000, University of Michigan
Bachelor of Science in Engineering, 1996, National Taiwan University

AREAS OF SPECIAL INTEREST:

Public realm planning and design, water and ecological planning and design, human aspects of environmental design, participatory design, water-sensitive urban design

PROFESSIONAL EXPERIENCE:

Co-Instructor, Intermediate Design Studio, Department of Landscape Architecture, University of Oregon, Spring 2015
Graduate Research Fellow, Informational Effect on Forest Perception, Department of Landscape Architecture, University of Oregon, Spring 2014
Graduate Research Fellow, Medieval and Contemporary Science Gardens, Department of Landscape Architecture, University of Oregon, Spring 2014
Co-Instructor, Undergraduate and Graduate Urban Design Terminal Studio, Department of Architecture, University of Oregon, Winter 2014
Graduate Research Fellow, Urban Design Lab, University of Oregon, Spring 2013
Co-Instructor, Undergraduate Landscape Architecture Terminal Studio, Department of Landscape Architecture, University of Oregon, Winter 2013
Roving Critic, Department of Landscape Architecture, Winter 2013
Instructor, Transformative Spaces Elective, Department of Landscape Architecture and Department of Dance, University of Oregon, Spring 2012

Partner, BioNova, 2012-2013
Research Assistant, Visual Neuroscience Lab, University of Oregon, 2011-2012
Research Assistant, Brain Electrophysiology Lab, University of Oregon, 2011-2012
Director, Om Creation Studio, LLC, 2007-2013
Studio Lead Designer, Urban Design and Landscape Architecture Studio, HOK Architecture & Planning New York Office, 2006-2007
Project Lead Designer and Manager, Design Studio, EDAW, Inc., Alexandria Office, 2001-2006
Graduate Student Instructor, Site Planning and Engineering, Department of Architecture, University of Michigan, Fall 2000
Landscape Architecture Intern, Design Studio, EDAW, Inc., Alexandria Office, Summer 2000
Graduate Student Instructor, Landscape Ecology Design Studio, Department of Landscape Architecture, University of Michigan, Spring 2000
Landscape Architecture Intern, Washtenaw Engineering Company, 1998-1999
Research Assistant, University of Michigan Transportation Research Institute, 1998-1999
Survey Manager, Ann Arbor Area Transportation Authority/Department of Urban and Regional Planning, University of Michigan, Summer, 1998
Research Assistant, Urban Security Group, University of Michigan, Fall 1997

GRANTS, AWARDS, AND HONORS:

Research Grant, Environmental Design Research Association, 2014-2015
Ministry of Education Scholarship, TECO, San Francisco, CA 2013-2015
Conference Scholarship, Environmental Design Research Association, 2014
Ph.D. Development Fund, Department of Landscape Architecture, University of Oregon, 2014
Ph.D. Development Fund, Department of Landscape Architecture, University of Oregon, 2013
Graduate (Dissertation) Research Fellowship, Department of Landscape Architecture, University of Oregon, Fall 2013, Fall 2014, and Winter 2015
Gary Smith Summer Development Award, University of Oregon, 2012
Conference Scholarship, Environmental Design Research Association, 2012
Cluster Fellowship, International Smart Geometry Conference, 2012
International Finalist, the Union Colony Civic Center Public Art & Water Feature, Greeley, CO, 2012 (Lead Designer and Public Artist with Om Creation Studio)
Promising Scholar Award, University of Oregon, 2011-2013
Berger Scholarship, Department of Landscape Architecture, University of Oregon, 2011
One Percent Green Recipient, Portland Bureau of Environmental Services, 2010 (Lead Landscape Architect and Public Artist with Om Creation Studio)

Conference Fellowship, Rail-Volution, Livable Portland, 2010
National Winner, Dorothy’s Place Public Art, Public Art St. Paul, 2010 (Lead Landscape Architect and Public Artist with Om Creation Studio)
Cultural STAR Grant, St. Paul City Council, 2010 (Lead Landscape Architect and Public Artist with Om Creation Studio)
Hankyung Grand Prize, New Songdo Central Park I Block 22, Incheon, Korea, 2009 (Lead Landscape Architect and Public Artist with HOK)
Potomac ASLA Honor Award, World of Wonders Children’s Garden, Norfolk, VA, 2008 (Project Lead Designer and Manager with EDAW)
Maryland ASLA Honor Award, World of Wonders Children’s Garden, Norfolk, VA, 2008 (Project Lead Designer and Manager with EDAW)
Potomac ASLA Honor Award, Wharf District Park, Boston, MA, 2008 (Project Designer and Assistant Project Manager with EDAW)
Northern Virginia AIA Merit Award, SallieMae Headquarters, Reston, VA, 2007 (Project Designer with EDAW)
Durham City-County Golden Leaf Merit Award for Community Properties, Museum of Life and Science “Explore the Wild” Exhibit, Durham, NC, 2007 (Project Lead Designer and Manager with EDAW)
National Winner, Arverne East Oceanfront Development Competition, New York Housing Preservation and Development, Queens, New York, 2006 (Lead Landscape Architect with HOK)
Carolinas Pinnacle Award, Museum of Life and Science, Durham, NC, 2006 (Project Lead Designer and Manager with EDAW)
Potomac Valley AIA Grand Honor Award, Katzen Arts Center at American University, D.C., 2005 (Project Designer and Manager with EDAW)
Washington D.C. AIA Merit Award, Katzen Arts Center at American University, D.C., 2005 (Project Designer and Manager with EDAW)
Inform Award of Honor for Landscape Architecture, Katzen Arts Center at American University, D.C., 2005 (Project Designer and Manager with EDAW)
Mid-Atlantic Construction Magazine Design Merit Award for Cultural, Museum, and Entertainment Category, Katzen Arts Center at American University, D.C., 2005 (Project Designer and Manager with EDAW)
National Finalist, Veterans Freedom Park Memorial Design Competition, Cary, NC, 2004 (Lead Designer and Project Manager with EDAW)
International Finalist, Beale Street Landing Competition, Memphis Waterfront Redevelopment Corporation, Memphis, TN, 2003 (Landscape Architect with EDAW)
National ASLA Analysis and Planning Merit Award, Michigan Department of Transportation Aesthetic Project Opportunities Inventory and Scenic Heritage Route Designation Inventory in Michigan, 2001 (Landscape Architecture Intern with Washtenaw Engineering Company)
Certificate of Honor, National Landscape Architecture Honor Society, 2000
Barbour Scholar Fellowship, University of Michigan, 1998-1999
Alumni Award, National Taiwan University, Taiwan, 1996
President’s Award, National Taiwan University, Taiwan, 1993-1996

PUBLICATIONS:

Rising, H. (2015). Water urbanism: The influences of aquaphilia on urban design. *Journal of Urban Design*. (Revise and Resubmit)

Rising, H. (2014). Placing "blue parkway" in the crosscurrents of water urbanism. *Building with Change: Proceedings of the 45th Annual Conference of the Environmental Design Research Association, p.315-316,* New Orleans, LA: Environmental Design Research Association.

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Rising, H. & Gillem, M. (2014). Mainstreaming water urbanism: In search of public acceptance for urban design interventions as climate change adaptation and sea level rise mitigation strategies. *Proceedings of the 2014 Council for Educators in Landscape Architecture Conference, p.305*. Baltimore, MD: Council for Educators in Landscape Architecture.

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CHAPTER I

COHERENT URBANISM THROUGH WATER URBANISM

DEFINITION OF TERMS

AQUAPHILIA AND WATER URBANISM

Many early human settlements originated in proximity to surface water bodies (Hampton, 2002; Hooimeijer, 2011). This desired adjacency could possibly be significantly motivated by aquaphilia, which literally translates into affection for water from the Latin aqua for water and philia, one of the four ancient Greek words for love. Inasmuch as aquaphilia implicates almost all human environments are arguably in proximity to water to the extent possible, <u>this research uses water urbanism to denote water-centric environment as a subset of water-based environments where water is intentionally integrated within urban fabrics as a substantial urban design element.</u>

WATER URBANISM AND AQUAPHILIC URBANISM

Specifically, water urbanism in this study refers to the systematic and more comprehensive integration of waterscapes with urban and suburban fabrics to produce water-centric environments with better synergies of urban form and health outcomes for individuals' body and mind. The term "aquaphilic urbanism" is proposed here to allude to the way in which water-based urban fabrics may facilitate the structuralist influence of aquaphilia on topophilia, that is, the development of environment-place bonds with water-centric environments. This statement is based on the assumption that these water-based urban fabrics are well designed to afford more aesthetically coherent spatial experience and perceptual schema than many conventional and technically pragmatic urban forms without or with little water-based design elements.

AQUAPHILIA AND BIOPHILIA

To investigate aquaphilia as an important aspect of individual agency for understanding self-determinism in the context of water urbanism, it is necessary to first spotlight the affinities of aquaphilia and biophilia. Biophilia has been commonly defined as people's unusual innate affection toward natural environments with a partial basis in evolutionary biology (Wilson, 1984). This genetically influenced emotional connection potentially contributes to our strong preference for the presence of survival-based advantages, including water, food, and defense in natural environments (Ulrich, 1993). Based on such a kinship between these two forms of attachment, this study defines this genetically predisposed notion of aquaphilia as human instinctual attachment to survival-enabling waters.

BEHAVIORAL AND STRUCTURAL INTERPRETATIONS OF AQUAPHILIA

This definition considers aquaphilia as a predictable response to specific water-based aesthetics associated with subsistence-based advantages in an urban environment, such as those related to the perceptions of scenes containing clean and safe waters. The author refers to this behaviorist interpretation of aquaphilia as pictorial aquaphilia. Pictorial aquaphilia can potentially be criticized as positivist and thus environmentally deterministic by structuralists who are more likely to perceive this survival-based aesthetics of water-based urban environments as the exchanges between urban design attributes and pictorial aquaphilia to evoke allocentric aquaphilia, that is, a structuralist notion of aquaphilia as an acquired human preference for water-centric urban environments.

Water-Resistant and Water-Coherent Urbanisms

"Water-resistant urbanism" and "water-coherent urbanism" are coined here for denoting two paradigms of water urbanism ideologies that shape planners' and designers' attitudes and approaches toward water: water-resistant urbanism, as a "land culture", tends to take a fight-or-flight approach to water as a threat. This urban design paradigm has frequently resulted in environmental, economic and social costs in addition to little perceptual and functional coherence, which is potentially cognitively associated with water in cities. In contrast, water-coherent urbanism or "amphibious culture" advocates living with water as a major urban landscape resource. This more amphibious public realm could potentially make cities more aesthetically and socially coherent. It could also help increase their adaptive capacities in the age of climate change and sea level rise by making them socially successful and more environmentally and economically harmonious with forces of nature.

BACKGROUND

Projected Increase in Climate Refugee Population

"When impacts of climate change fully take hold", there could be as many as 200 million or more environmental refugees "overtaken by sea–level rise and coastal flooding, by disruptions of monsoon systems and other rainfall regimes, and by droughts of unprecedented severity and duration (Wilson, 1993)." It is likely that this projected number of environmental refugees may be even greater, because by 2030, half of the global population is projected to be within 100 km of ocean coasts with increasing flood risks due to climate change and sea level rise (Adger, Hughes, Folke, Carpenter, & Rockström, 2005).

Environmental Adaptation of Voluntary Migrants in Safer Locations

In contrast to this predicted migration trend toward danger, climate change impacts have had an increasing influence on voluntary migration, although many other factors also underlie migration decisions (Black, Adger, et al., 2011). In fact, temporary and permanent migration to safer places has been deemed the most effective means for individuals to adapt to potentially life-threatening environmental changes in developing countries (Black, Bennett, Thomas, & Beddington, 2011; Laczko & Aghazarm, 2009). These safer areas are thus likely to have newer and more transient populations as the impacts of climate change continue to unfold. Climate change adaptation analysts have also recognized a higher preference for individuals to voluntarily relocate and the need for a greater attention to the migrants' environmental adaptation after their relocation (Penning-Rowsell, Sultana, & Thompson, 2011). One way to facilitate voluntary migration is to provide basic infrastructure to enable relocation and settlement in these safer areas in a sustainable way (Black, Bennett, et al., 2011). No study has investigated how safer destinations can be better designed to facilitate the environmental adaptation of newcomers.

Mismatch of Jobs and Populations for Water Amenity-Driven Voluntary Migration

Similarly, compared with emergency evacuation and displacement prevention, voluntary migration has been recommended as a more holistic approach to adaptation and disaster planning for developed countries (Savvas, 2003). Unlike developing nations, where voluntary migration has become increasingly driven by individuals' desires to circumvent climate change impacts, voluntary migration in developed countries has been progressively influenced by proximity-seeking to natural amenities among those individuals with growing wealth (Howe, McMahon, & Propst, 2012).

Nord and Cromartie (1997) define natural amenities as moderate, sunny winters and summers with low humidity, as well as diverse topography with mountains and abundant water. With the exception of water, other natural amenities cannot easily be created by humans. In addition, natural amenities, water-based resources in particular, significantly explain economic and population growth (Deller, Tsai, Marcouiller, & English, 2001; Marcouiller, Kim, & Deller, 2004). Such a water amenity-driven migration pattern has, however, been thought to potentially increase unemployment, as rural water amenities did not seem to increase employment opportunities (Deller et al., 2001). At the same time, Cohen (2000) noted that an increasing number of jobs had been migrating to high-amenity cities due to theses cities' appeal to well-educated workers in search of amenities as one key relocation consideration.

Combined with other migration incentives, such as employment opportunities or tax breaks, the implementation of upstream and inland water urbanism may help contribute to a greater long-term positive pull toward safer high grounds in currently amenity-poor upstream and inland cities. This integrated and proactive approach to voluntary migration could potentially help inland and upstream cities attract more individuals and businesses, minimizing involuntary displacement and damage to lives and properties in downstream and coastal areas faced with increasing climate change impacts.

Positive Pull and Negative Push Factors of Environmental Preference

Korpela (1989) noted that immigrants often sought out water bodies to facilitate a process of environmental self-regulation and to reduce stress associated with being in an unfamiliar environment. This dissertation investigated the influence of aquaphilia, that is, instinctual human affection toward water or water-centric environment, on topophilia, which Tuan (1974, p. 93) defines as human "affective ties with the material environment." This water-based place attachment may be one important pull factor for environmental preference. According to Rapoport (1977), people are inclined to choose environments due to their positive pull factors and avoid settings that embody negative push factors, and such an environmental preference influences migration and habitat selection as a response. Brown and Moore (1970) refer to migration as the decision to seek a new residence and habitat selection as the relocation decision. They postulate that the migration decision is largely influenced by household perception of stressors as a negative push and their capacity to cope with stress *in situ* as a positive pull. The author speculates that the ability of these households to regulate stress through environmental adaptation could be supported by the presence of some positive-pull-generating spatial components, such as water.

A Growing Need for Upstream Water-Retention

Climate change has resulted in more extreme rainfall and more sustained droughts. The rising sea level has also increased the imminent flood risks for downstream and coastal areas, which are most vulnerable to flash floods caused by increasingly impervious upstream watershed areas and extreme storm events. The increasing peak runoff discharges from upstream cities and the growing scarcity of water supplies necessitate greater upstream and inland retention capacities to prevent floods and mitigate droughts.

As most dam-suitable sites have already been put to use, these additional retention capacities may require the use of a decentralized network of small-scale water retention areas, which are a more water-coherent form of green infrastructure.

A WATER-COHERENT IMPETUS IN GREEN INFRASTRUCTURE MOVEMENT

Green infrastructure traditionally refers to interconnected networks of parks, greenways, open spaces, and other natural landscape elements, which are essential components of urban environments' community benefits (Benedict & McMahon, 2006; Kambites & Owen, 2006). Waterways have increasingly been regarded as the skeletons of many systems of green infrastructure (Shafer, Scott, Baker, & Winemiller, 2013) and have become more explicit in the following definition of green infrastructure: greenery and open spaces linked by streets, waterways, and drainage ways around and between urban areas at all spatial scales (Tzoulas et al., 2007). However, this definition implies that waterways go around and between urban areas as opposed to being integrated with urban fabrics. Beatley and Newman (2013) propose this more water-coherent approach to green infrastructure as a primary pathway through which biophilic urbanism contributes to climate change mitigation and adaptation. Biophilic urbanism is an urban design approach that uses nature as a main driver for city planning, design, and management. According to Beatley and Newman (2013), this climate-induced water-coherent impetus in biophilic urbanism may have helped engender an increasing number of stream daylighting projects. Although these stream daylighting projects have remained largely linear rather than networked, their positive impacts on downtown revitalization indicate water as a potentially important driver for urban design (Doran & Cannon, 2006; Lah, 2011).

An Emerging Water-Coherent Urbanism for Upstream and Inland Cities

"Living with water" has recently been adopted as a new approach to systematically integrate water management with urban fabrics for reducing peak runoff volume downstream. This water-coherent approach to urban design is more cost-effective when implemented upstream and inland, as opposed to downstream along the coast, in the deltas, and near floodplains (Hartmann, 2009). Furthermore, this approach could potentially make inland and upstream cities more attractive to water amenity-driven migrants, including new businesses, educated workers, and environmental refugees from flood-prone cities. There has been no prominent discourse for a water-coherent approach to systematically integrating water into inland and upstream cities. While many factors contribute to migration choices by individuals and businesses, safer loci of attachment due to aquaphilia, that is, instinctual human affection toward water or water-centric environments should be studied as one potentially important factor. The potential of water-coherent urbanism to produce more environmentally, economically, and socially coherent urban designs may contribute to better-adapted inland and upstream cities as climate change and sea level rise continue to cause many cities to both grow and change their forms.

The Image of the Water City

The title of this dissertation, *Water Urbanism: Building More Coherent Cities*, forefronts its aim to beget a more coherent city image with water urbanism. To this end, the primary focus of this study is on the development of an approach to composing an iconography of water urbanism. This iconography of water urbanism was envisioned by the author to encompass specific ways to integrate water with urban and suburban fabrics to evoke a more coherent city image through the enhancement of genius loci. The author postulated that such heightened water-based sense of place may in turn evoke allocentric aquaphilia. This structuralist influence of aquaphilia on topophilia is a form of water-based place attachment, that is, human-environment bonds acquired through transactional experiences with water-centric environments. While instinctual human attachment to water is due in part to evolutionary biology (Coss, 1990) , the empirical investigation of this genetically influenced human response to water is outside of the scope of this dissertation.

AQUAPHILIA AS THE FUNCTION OF AESTHETIC COHERENCE IN ADAPTATION

Overall, this research argues that the imageability, that is, the aesthetic coherence, of a water city could potentially facilitate the environmental adaptation of individuals to evoke allocentric aquaphilia as water-based place attachment to water-centric cities. Allocentric aquaphilia as the outcome of an aquaphilic urbanism, in turn, may help mainstream water-coherent urbanism in upstream and inland cities, making them more environmentally coherent. The author coined "coherent urbanism" to refer to an arguably less dichotomous urban design paradigm than other previous and predominant functional models for city-making. Specifically, coherent urbanism foregrounds the urban picturesque approach to engender a more aesthetically coherent city image. The aesthetic coherence of city image is conceptualized as a means to evoke a more emotionally coherent aquaphilic urbanism, which, in turn, helps adapt individuals and cities to a more environmentally coherent functional model, such as water-coherent urbanism.

ALLOCENTRIC AND EGOCENTRIC PERSPECTIVES OF AESTHETIC COHERENCE

According to Raynsford (2011), Lynch (1960) intentionally omitted references to the works of other urban picturesque theorists in *The Image of the City* and grounded his theoretical interpretations in perceptual psychology, environmental anthropology, and even animal behavior research. Researchers from these disciplines and other social science fields, such as behavioral geography and neuroscience, subsequently provided empirical evidence for allocentric coherence as two-dimensional configurational knowledge exhibited in people's cognitive images. Imageability, Lynch's term for legibility, not only refers to this gestalt quality in people's map-like cognitive image from an allocentric perspective but also to a coherent sequence of eye-level scenes as a form of egocentric coherence.

Aesthetic Coherence from the Picturesque Tradition

Although Lynch (1960) might have introduced the concept of allocentric coherence as the perception of imageable cities to the urban design literature, the idea of egocentric coherence had long been incubated in an established picturesque tradition for urban aesthetics. In the 18th-century empirical theories of aesthetics, picturesque was regarded as a mediator between beauty and sublime. These two opposing aesthetic ideals, namely, beauty and sublime, correspond with the feelings of pleasure and security associated with the needs for stimulation and self-preservation (Burke, 1998). Concurrent to this discourse of landscape aesthetics was an increasing focus on the irregularity of nature in landscape design as a reaction to the formal geometries of French landscape. Specifically, landscape painting principles were applied to the design of three-dimensional spaces to qualify a well-designed garden as one that affords "a journey through a succession of pictures" (Fabricant, 1979, p. 112). The adaptation of the landscape picturesque tradition for European medieval towns can be traced back to the "street picture," made popular by Raymond Unwin (Raynsford, 2011, p. 48). The picturesque perspective suggests that legible urban forms produce salient "street pictures," which encompass prominent objects (to anchor the eyes) and contrasting elements (for the mind to make associations). As a genre of representation, good "street pictures" are eye-level, one-point perspectives that provide a viewer with "a stable set of spatial co-ordinates" about a perceived urban space, including scales, distances, and directions (Raynsford, 2011, p. 48).

An Urban Picturesque Theory of Emotional Coherence

Isaacs (2000) proposes the urban picturesque theory, suggesting that urban forms derived from the landscape picturesque tradition could generate a universal aesthetic appeal to potentially help encourage more pedestrian activities. The urban picturesque theory implied that the unfolding of different scenes as eye-level perspectives could potentially motivate proximity-seeking behaviors. Sitte (1945, p.1) believes that the aesthetic principles he proposes in *The Art of Building Cities* would make urban inhabitants sense "waves of harmony like the pure tones of sublime music" as emotional security and happiness. This sense of harmony appeared to be associated with the notion of cinematic coherence, as Sitte (1945) emphasizes the unfolding of an ever-changing eye-level scene as a key criterion for an aesthetically appealing urban form. In highlighting the significance of Sitte's iconographic approach to city-making, Walker (1945) suggests that cities without the aesthetic and emotional qualities that people find vital in visual art might fail to encourage citizen participation, thereby prompting citizens to seek other cities with these qualities. Although many socioeconomic factors affect habitat selection decisions, Walker's observation implies the aesthetic coherence of cities is one motivational pull that helps people emotionally cohere to a city.

In Search of a Postmodern Urban Design Experiment

This coherent approach to urbanism may be one possible way to instigate a necessary postmodern turn in response to the arguably more dichotomous nature of past and present models of city-making. Many of these urban design paradigms have often been considered environmentally deterministic, an umbrella term that may potentially imply either one of the following four distinct aspects: 1) environmental determinism (with respect to forces of nature) refers to nature's dominance over cities' capacity for self-determination to sustain their existence (Pelton, 2005); 2) technological determinism (in regards to supremacies of technology) alludes to a promethean view that considers forces of nature conquerable with technology and technology a necessity for modern cities' survival (Frenkel, 1994); 3) physical determinism (with reference to the use of large-scale physical solutions for social control of select populations) denotes a top-down urban design approach that can jeopardize the individual agency of disadvantaged communities to enable the survival of others during social and environmental crises in industrializing cities (Hirt, 2012; Vischer, 2001; Zukin, 2007); 4) behavioral determinism (relating to environmental conditioning versus human free will) concerns the use of a positivist or behaviorist approach in environment-behavior studies to objectify humans as having predictable responses to environmental stimuli, with little consideration of free wills, subjectivity, and individual differences (Mitchell, 1974).

Determinism as Conundrum of Designing an Emancipating Public Realm

Many postmodern attempts to realize coherent urbanism started with reimagining the discourse of public realm design from its tainted past of environmental determinism. Most of these efforts have been united under a common goal to emancipate individual agency from deterministic forces in order to enhance cities and individuals' capacity for self-determination in service of both collective and individual survival (Cosgrove & Jackson, 1987). This collective aim engendered the birth of environment and behavior research that applies theories and methods of environmental psychology and behavioral geography to inform environmental design. Yet, these postmodern revolutionary endeavors seem to have been undertaken as partial reactions to only some of these aforementioned four aspects of determinism, potentially resulting in a dichotomous intellectual landscape. For instance, while behavioral determinism may have instigated the emergence of a humanistic approach that is apt to focus on subjectivity and individually differentiated perceptions, few empirical studies have synergized positivist and humanistic approaches. On the contrary, place research has encountered a growing divide between humanistic and positivist approaches that prevents either approach from being effective (Lewicka, 2011).

Some of the reactionary approaches to environmental determinism have become new opposing forms of determinism in the absence of complete resolutions for human-nature incoherence. For instance, new urbanism and landscape urbanism provide two divergent perceptions toward the roles of density and nature in humanizing the urban environment (Talen & Duany, 2013). Landscape urbanism may have been a response to environmental determinism with respect to forces of nature. Yet it has been deemed ecologically deterministic because landscape urbanism advocates the use of ecological conditions to inform environmental changes in less developed areas. For urban areas, landscape urbanism, as a city-wide application of green infrastructure, reintroduces open spaces as restructuring devices for deindustrialized cities to increase their adaptive capacities in the face of more extreme rainfall events and other climate change impacts. By prioritizing landscape as the dominant urban design driver, landscape urbanism can sometimes be at the expense of a necessary density required to support a safe and human-scaled public realm (Corner, 2012; Schensul & LeCompte, 1999; Talen & Duany, 2013). New urbanism, on the other hand, may have been a reaction to physical determinism as indicated by its attempts to humanize large-scale top-down physical interventions as social solutions. However, new urbanism has been considered a physically and behaviorally deterministic approach, owing to its intent to rely on environmental alterations to instigate expected behaviors and meet human needs (Gordon, 2002). Granting landscape urbanism and new urbanism may have emerged as responses to environmental determinism, they have been arguably referred to as environmental determinism when ecological and physical principles are applied to public realm planning in a top-down technocratic fashion to address economic, social, or environmental problems (Graham & Healey, 1999; Karvonen, 2011; Maslow & Lewis, 1987; Pelton, 2005; Schensul & LeCompte, 1999).

Many previous urban design paradigm shifts led to the majority of contemporary urban forms. For instance, most cities bulldozed much of the fine-grained parts of their public realm to accommodate automobile traffic when the mass production of personal vehicles became possible. The advent of an underground sewer system transformed most urban forms into water-resistant land developments with a large amount of impervious surfaces. The Congrès internationaux d'architecture moderne (CIAM) rapidly popularized the functionally segregated modernist urbanism around the world. In contrast, most postmodern revolutionary endeavors, such as new urbanism, landscape urbanism, and ecological urbanism, have often had to exorcise the ghost of environmental determinism and have thus remained relatively limited in scope and impact. This may be attributable to the stigmatization of public realm design as deterministic by previous top-down urban design revolutions such as Baron Haussmann's urban renovations in Paris, modern urbanism in the lineage of CIAM, the City Beautiful Movement, and post-war urban renewal in the United States.

LESSONS LEARNED FROM PREVIOUS POSTMODERN URBAN DESIGN EXPERIMENTS

Nonetheless, there were many successful small-scale postmodern urban design experiments initiated through evidence-based design research. Some noteworthy examples include 1) the emergence of crime prevention through environmental design (CPTED) as a research field to address crimes in decaying neighborhoods and urban cores (Newman, 1972); 2) the effort of Clare Cooper Marcus to humanize postwar housing and public spaces with insights from post-occupancy evaluations (Marcus & Francis, 1997; Marcus & Sarkissian, 1988); 3) Kevin Lynch's city image research for prescribing urban design interventions for Boston, Jersey City, and Los Angeles (Lynch, 1960); 4) Donald Appleyard's (1976) sketch map scoring methods for investigating ways to design for a pluralistic city; as well as 4) New York city's zoning changes initiated by William Whyte and the Project for Public Spaces through conducting participant observations in small urban spaces (Whyte, 1980). These evidence-based design approaches may be considered inevitably deterministic by some, due to their intent to prescribe design approaches for large-scale environments in the public realm. In addition, their increasing growing concern for validity and reliability can be perceived as a form of behavioral determinism, which favors a positivist or behaviorist approach based on the stimulus-response paradigm. This paradigm implies the predictability of collective responses to environmental stimuli, thus relegating free wills, subjectivity, and individual differences to potential confounds.

On the contrary, a user-centered urban design experiment was instigated with the use of participatory processes to help obtain green light in face of potential postmodern attacks on the grounds of environmental determinism (Frediani & Boano, 2012). Such a commonly revered and potentially politically correct approach has a persuasive appeal to postmodernists possibly because its upfront goal, which is to engage individual agency in reforming urban design, appears to help address environmental determinism as the conundrum of an emancipating public realm. This is despite this participatory approach's potential danger to favor the self-preservation agendas of activists that are often less disadvantaged than voiceless segments of society. Disadvantaged populations may be designed out of a participatory process for large-scale environments as a result of their frequent absence or lack of resources to affect environmental decisions (Platteau, 2008). In light of these lessons learned, this study deployed an evidence-based research design to engage participants to share their transactional experiences with water cities. This research design mixed both humanistic/structuralist and positivist/behaviorist methods to probe both subjectivity and objectivity inherent in people's environmental perceptions and preferences. Such a mixed-methods approach aspires to identify collective patterns from individual idiosyncrasies in environmental images to inform public realm design for the benefits of all to the extent possible.

MAINSTREAMING URBAN DESIGN EXPERIMENTS WITH CITY IMAGE COHERENCE

Environmental image is a cultural and psychological iconographic phenomenon associated with people's environmental perceptions and preferences. As an environment-behavior research area, it has involved researchers from environmental design, environmental psychology, behavioral geography, and neurophysiology (Moore & Golledge, 1976). This research area has the potential to engage both behaviorist and structuralist approaches, dissolve the objectivity-subjectivity divide, and blur disciplinary boundaries to enable interdisciplinary synergies.

Many humanists regard environmental image as entirely pluralistic and subjective. This standpoint may be inclined to use determinism to describe any effort to identify collective patterns from individuals' environmental images to inform public realm design. The extreme version of this standpoint was well articulated by Huxtable (1973): There are as many potential images of the world as there are eyes and minds to frame and interpret them… images of the environment inevitably structure reality…Our urban concepts are defined by certain key photographic images… (p. 26)

However, a descriptive or artistic approach to investigating environmental image may be deterministic. Specifically, this approach only presents the environmental images of select elites, such as humanistic researchers, artists, photographers, and documentary makers, to represent an environment imbued with the lived experience of common people. To behavioral geographers interested in studying participants' environmental images for public realm applications, this pluralistic and subjective view of environmental image at best suggests a possible middle-ground. In other words, probable patterns may emerge from similarities within specific user groups differentiated by socioeconomic factors, including age, education level, gender, income level (Moore & Golledge, 1976). However, a collective environmental image for a large-scale environment may still signify a somewhat deterministic attempt in the eyes of behavioral geographers.

At the same time, a number of environmental design researchers engaged a similar approach to environmental images in the context of participatory design. This approach could be perceived as somewhat deterministic because it intends to distill from individuals' environmental images a collective city image with public realm design implications. For example, urban design researcher Kevin Lynch qualitatively condensed a collective city image from participants' sketch maps, in addition to results of photograph recognition and interviews. This collective city image then became the basis for prescribing urban design interventions for the participants' respective city (Lynch, 1960). Based on classifications of the topologies observed in sketch maps that were collected from Ciudad Guayana, Donald Appleyard suggested the potential existence of urban design guidelines applicable for multiple pluralistic cities (Appleyard, 1976). Appleyard's more deterministic gesture could be attributable to his use of a seemingly more positivist, quantitatively oriented or objective research design to analyze sketch maps. His research design was composed of a scoring rubric for categorizing sketch maps, a statistical method (called analysis of variance) for analyzing sketch map differences between socioeconomic groups, and a larger sample size than those used for Lynch's studies in Boston, Jersey City, and Los Angeles. More recent environmental image research conducted under the lens of neurophysiology suggests the potential existence of non-locality-specific collective patterns for describing the nature and formation of environmental images (Epstein & Vass, 2014). The findings could potentially generate a more positivist thrust to the study of environment image in the fields of behavioral geography and environmental psychology. This dissertation is an example.

This brief review of environmental image research potentially implicates the existence of a non-locality-specific and evidence-based shared iconography of water urbanism as a genre of urban design. This iconography may be dissected into a water city's choreographic (two-dimensional structure), phenomenological (three-dimensional composition), and narrative components (non-imageable impressions and ideologies). This iconography of water urbanism may be extracted from people's environmental images of water cities to help us understand possible ways to enhance a city's sense of place with water urbanism.

WATER-COHERENT URBANISM – A PROMISING FORM OF COHERENT URBANISM

This dissertation sets forth a conscious decision to frame water-coherent urbanism as a promising form of coherent urbanism. Water-coherent urbanism was invented to denote a specific type of water urbanism located inland and upstream with the premise of living with water as a resource. This research postulates this form of coherent urbanism may be more likely to rise to the challenges of globalization and climate change than the predominant urban design models in use today.

By reason of water's essential role in human existence and many cultures, water urbanism has a traceable pedigree with an extensive history since antiquity. Nevertheless, this probable homecoming journey can only shed as much light on a destined metamorphosis of cities to the extent that we are ready to conceive the likelihood of an impending abyss due to the failure of current urban design paradigms and water-resistant infrastructure to tackle contemporary challenges of globalization and climate change.

STUDY OBJECTIVES

This dissertation argues that the imageability of a water city could mediate the relationship between water density/watershed location and allocentric aquaphilia, that is, the structuralist influence of aquaphilia on topophilia. This water-based place attachment to a water-centric city may mediate the relationship between the city's imageability and water-coherent urbanism. These two hypotheses aimed to support a potential theory of aquaphilic urbanism, where a water-based sense of place helps engender a more sustainable water-based place attachment to upstream and inland cities by making these cities more aesthetically, emotionally, and environmentally coherent loci of attachment. To link aesthetic with emotional coherence, this study examines allocentric aquaphilia, that is, water-based place attachment at the city level, as one key perceptual aspect of aesthetic coherence, which could be the best potential achievement of water urbanism. For relating emotional with environmental coherence, this research studies the potential of allocentric aquaphilia to instigate public acceptance of water-coherent urbanism as a more sustainable and powerful basis of attachment.

PROJECT SIGNIFICANCE

This study demonstrates the feasibility of a multi-sited, mixed-methods research design for exploring public perceptions toward possible ways to build more coherent and thereby sustainable cities through water urbanism. When this research design is applied to a greater number of participants and a more diverse array of water cities in future studies, it may help generate a collection of evidence-based design guidelines for building more coherent cities as an iconography of water urbanism. These aquaphilia-evoking urban design guidelines could make relatively placeless suburbs and cities located in safer inland

and upstream areas more attractive and viable loci of attachment for new businesses, educated workers, and environmental refugees, thereby making these suburbs and cities more coherent aesthetically, emotionally, environmentally, economically, and socially.

SITE SELECTION

This study uses precipitation pattern similarity and geographical proximity as selection criteria to identify eight water cities from all water cities known as “Venice of the North”: Amsterdam, Rotterdam, Almere, and Giethoorn in the Netherlands, Ghent and Bruges in Belgium, and Berlin and Hamburg in Germany. Geomorphology and water density also differentiate these eight water cities into two subgroups for comparison in Chapter V: coastal and downstream water cities versus inland and upstream water cities. Although all eight water cities have canals, coastal and downstream water cities have a water density greater than 10%, because of the presence of larger bodies of water such as harbors and lakes. The water density for the sampled inland and upstream cities is less than 10%.

CHAPTER DESCRIPTIONS

CHAPTER I – COHERENT URBANISM THROUGH WATER URBANISM

This introductory chapter presents an overview of problem statement, project significance, definition of terms, study objectives, dissertation organization, site selection, sampling, as well as chapter descriptions, including research questions and research methods. It also introduces the central concept of “image of water city” as a potential means to engender coherent urbanism using a user-centered, evidence-based research design. This chapter also delimits a fully elaborated iconography of water-coherent urbanism as a long-range goal beyond the scope of this study. However, the long-term development of this iconography may be aided by this study because they are both concerned with the same question of how to build more coherent cities with water urbanism. This study intends to develop a feasible research design to begin to answer this overarching question by dissecting it into a number of sub-questions, each of which is addressed in Chapters II, III, IV, and V.

CHAPTER II –WATER URBANISM: THE INFLUENCES OF AQUAPHILIA ON URBAN DESIGN

The author performed a review of urban picturesque literature to investigate coherence and aquaphilia based on pictorial, egocentric, allocentric, and emotional perspectives. This literature review also identified nine urban design attributes as evaluation criteria for content analysis of the following data: 1) participants' responses for what they liked or did not like about the existing water network, and 2) participants' reasons for each feature that emerged during their cognitive mapping, photovoice, and emotional recall procedures for the city where they were sampled. Chapter II attempted to respond to the sub-question of how pictorial aquaphilia, as the behaviorist notion of aquaphilia, interacts with urban design attributes to produce aquaphilic urbanism that evokes egocentric and allocentric aquaphilia, that is, the structuralist influence of pictorial aquaphilia. The ultimate purpose of this chapter is to identify promising research designs and measures for subsequent quantitative research, including testing Lynch's theory of imageability in water-centric cities (Chapter III) and modeling the influence of allocentric aquaphilia on topophilia (Chapter IV).

CHAPTER III –THE IMAGE OF THE WATER CITY: TESTING THE IMAGEABILITY THEORY FOR STRUCTURING THE PLURALISTIC WATER CITY

Through regression analyses, Chapter III investigates the potential contributions of waterscape attributes to imageability, that is, the aesthetic coherence of aquaphilic urbanism, while accounting for the potential intervening effects of a participant’s status as a visitor versus resident, aquaphilia sensitivity baselines, and socioeconomic backgrounds, including gender, age, education level, and income level. Theoretically, this chapter used spatial cognition theories from behavioral geography to combine Appleyard’s sketch map scoring method with Lynch’s theory of imageability for empirically testing possible ways to design pluralistic cities through the image of the water city.

Specifically, this chapter targets five types of waterscapes that correspond to Lynch’s five elements of imageability, which are landmarks, paths, nodes, edges, and districts. These five waterscape types are water landmarks, canals, lakes, rivers, and harbors. Water landmarks refers to salient features or scenes across or along water bodies. For each waterscape type, mappability, identifiability, and attachment were included as possible contributors to the aesthetic coherence of aquaphilic urbanism. These three waterscape attributes accounted for each waterscape type’s allocentric, egocentric, and emotional salience in participants’ recall memory related to Lynch’s three components of imageability: structure, identity, and meaning. The perceived imageability or aesthetic coherence of aquaphilic urbanism was measured by the coherence of participants’ sketch maps. The coherence level of spatial cognition is argued to be associated with the aesthetic coherence of water urbanism for participants capable of fairly representing their environmental comprehension as sketch maps.

The first half of Chapter III strives to obtain a reliable measure for assessing the coherence of the 55 sketch maps collected from 60 participants sampled from eight water cities according to dual-view, allocentric, and egocentric perspectives. For assessing the sketch maps' dual-view coherence, the investigator recruited two independent raters to score each sketch map using a proposed rubric based on the types of spatial knowledge presented by the map. Unlike Appleyard's empirically-derived rubric based on a typological observation of sketch maps, the sketch map evaluative rubric in this study was informed by spatial behavior literature in behavioral geography to provide content validity for each rubric category. Due to divergent theoretical stands on the development of spatial cognition, two scoring schemes were put forth and tested to code the rubric ratings based on six versus eight stages of environmental comprehension. A third scoring scheme was also included to acknowledge nuances within the eight stages of spatial knowledge by adding four additional stages to account for the potential confounding effects of varying graphic production skills among the participants.

The investigator then colored the water elements in the sketch maps in blue for evaluation by two additional independent raters to derive the measures for the sketch maps' water-based allocentric and egocentric coherence. For water-based allocentric coherence, the investigator asked the raters to glance at eight city maps for no more than ten seconds before they attempted to identify the city associated with each colored sketch map. The correct and incorrect map identification was coded as 1 and 0 to generate base scores to be weighted by the extent to which water helps with map identification, which was another indicator obtained through a separate question. To measure water-based egocentric coherence, the investigator instructed the raters to assess the degree to which non-blue features cluster along blue features in a different question. Inter-rater reliability tests were conducted to identify reliable coherence measures for use as dependent variables in regression analyses in the second half of the chapter.

The second half of Chapter III conducts regression analyses using the proven reliable coherence measures as dependent variables and waterscape attributes and socioeconomic factors as independent variables. For each coherence measure as an independent variable, the investigator first uses stepwise subtractive regression analyses to identify waterscape attributes that significantly improves the regression models for the base models. Stepwise additive regression analyses are then conducted by adding one socioeconomic variable at a time to the base models to identify socioeconomic variables that significantly improve the regression models for the final models. The final regression models help discern waterscape attributes and socioeconomic factors with significant effects on each coherence measure or intervening effects on each other in explaining coherence. This chapter provides empirical evidence to answer the question of how waterscapes contribute to the perceived coherence of a water city image for both visitors and residents with varying aquaphilia sensitivity baselines and socioeconomic backgrounds, including gender, age, education, and income.

CHAPTER IV – AQUAPHILIC URBANISM: WATER-BASED SPATIAL ANCHORS AS LOCI OF ATTACHMENT

In Chapter IV, the author uses path analysis to test three competing theoretical models of attachment from social psychology and environmental psychology against empirical data from the same participants. This model comparison identified a best-fitting model for operationalizing allocentric aquaphilia, that is, the structuralist influence of aquaphilia on topophilia as a form of water-based place attachment. Specifically, allocentric aquaphilia was modeled as an outcome variable of four interrelated aspects of a water-based sense of place based on a functional perspective of urban picturesque aesthetics. These four constructs of allocentric aquaphilia were water-based familiarity, water-based comfort, water-based place dependence, and water-based place identity.

Anchorpoint theory from behavioral geography was used to translate the social-psychological theory of attachment into the context of wayfinding. This wayfinding perspective was used to explain people's psychological need to maintain proximity to water-based spatial anchors as prominent features, instead of salient figures, as in interpersonal attachment, due to the sense of familiarity and comfort provided by water-based spatial anchors. Similarly, the author used the same wayfinding standpoint to interpret the three constructs in the tripartite environmental-psychological theory of place attachment, place identity, and place dependence as the extent to which water-based spatial anchors provided emotional bonding, a sense of identifiability, and a sense of orientation.

This chapter addresses the following question of particular interest to landscape architects and urban designers who strive to design the public realm to evoke a sense of place for all: How do the functional aspects of water aesthetics in wayfinding, that is, attributes of water-based spatial anchors, contribute to the structuralist influence of aquaphilia on topophilia as acquired human attachment to water-centric environments?

CHAPTER V – AQUAPHILIA: THE FUNCTION OF AQUAPHILIC URBANISM FOR ADAPTATION

Chapter V demonstrates the coherent image of a water city as a potential means to mainstream water-coherent urbanism for public acceptance: by conducting mediation analyses with variables derived from Chapters III and IV, this chapter investigates whether the perceived imageability or aesthetic coherence of aquaphilic urbanism mediates the relationship between water densities/watershed locations and allocentric aquaphilia to help adapt cities and individuals to an upstream and inland water-coherent urbanism as a more environmentally, economically, and socially coherent locus of attachment than water-resistant urbanism.

In the first section of Chapter V, the investigator performs principal components analyses to reduce four functional aspects of aquaphilic urbanism in Chapter IV into two wayfinding factors, which are water-based imageability (as a component for water-based familiarity and water-based place identity) and water-based goal affordance (as a component for water-based comfort and water-based place dependence). These two wayfinding factors were further reduced into aquaphilic urbanism as a component for all four measures.

The investigator then conducts macro-level mediation analyses to investigate whether each of these three components, namely, water-based imageability, water-based goal affordance, and aquaphilic urbanism, mediated the effect of cities' water densities/watershed locations on allocentric aquaphilia. Another set of macro-level mediation analyses are performed with allocentric aquaphilia as a possible mediator for the relationship between each of the three components as independent variables and openness toward water-coherent urbanism as the dependent variable. The measure for openness toward water-coherent urbanism was obtained from a number of questionnaire items associated with water-coherent urbanism. This second set of macro-level meditation models examined allocentric aquaphilia as the function of aquaphilic urbanism for adapting cities to inland/upstream water-coherent urbanism.

The last section of this chapter uses two groups of micro-level mediation analyses to study waterscape attributes as probable intervening influences for the effects of gender and visitor versus resident on coherence measures while controlling aquaphilia sensitivity baseline. These waterscape attributes include the measures of waterscape mappability, waterscape identifiability, and waterscape attachment for each of the five waterscape types, namely, canals, harbors, lakes, rivers, and water landmarks. Dual-perspective coherence, water-based allocentric coherence, and water-based egocentric coherence from Chapter III are used as coherence measures.

Chapter V responds to the question of how components of aquaphilic urbanism, or the perceived aesthetic coherence of water urbanism help adapt individuals and cities to inland/upstream water-coherent urbanism. This question often preoccupies planners, designers, policy makers, and geographers concerned with public acceptance of retrofitting urban fabrics with water-coherent urbanism as a more sustainable form of cities and locus of place attachment.

CHAPTER VI – TOWARD AN ICONOGRAPHY OF WATER URBANISM

Chapter VI provided conclusions for this dissertation by summarizing findings from previous chapters, identifying possible theoretical and empirical contributions to the literature of the urban picturesque, discussing research limitations, and suggesting future research directions. It also put forward some potentially promising iconographic components of water urbanism for building more coherent cities by triangulating results from previous chapters.

INTERRELATIONSHIPS AMONG CHAPTERS REPORTING EMPIRICAL INVESTIGATIONS

Chapters II, III, IV, and V focus on empirical investigations with individuals as primary units of analysis using the same field data from 60 participants sampled from eight water cities. Overall, these chapters answer the aforementioned research questions by conceptualizing allocentric aquaphilia and aquaphilic urbanism as hypothesized models for empirical testing. They function as different data analysis phases, using complementary methods to help triangulate results across chapters. For example, Chapter II content analyzes field data to identify promising research designs and measures for use in Chapters III-V. The regression models and variables derived from Chapter III helped identify the potentially significant relationships between gender and the group variable of visitor versus resident and select coherence measures, in addition to the probable intervening effects of waterscape attributes. However, these effects could not be confirmed in the presence of people's aquaphilia sensitivity baseline's significant effect on all coherence measures for all regression models. Micro-level mediation analyses in Chapter V allows aquaphilia sensitivity baseline to be controlled as a covariate to target specific waterscape attributes as potential mediators of specific group effect on coherence measures. Chapter III also tests the reliability of coherence measures for use in the mediation analyses in Chapter V.

The model derived from Chapters IV sets the stage for two macro-level research agendas in Chapter V: 1) testing whether aesthetic coherence (as aquaphilic urbanism or its aesthetic and functional subcomponents) mediates the relationship between environmental factors (the effect of water density/watershed location) and emotional coherence (in the sense of allocentric aquaphilia); and 2) testing whether emotional coherence (as allocentric aquaphilia) mediates the influence of aesthetic coherence (in the sense of aquaphilic urbanism or its aesthetic and functional subcomponents) on environment coherence (in the form of upstream and inland water-coherent urbanism).

For Chapters II-V, the author employs a mixed-methods data collection protocol in order to empirically test the ways in which water aesthetics related to allocentric aquaphilia, aquaphilic urbanism, and water-coherent urbanism as possible theoretical models. Table 1.1. provides an overview of model variables and their respective measures.

Table 1.1.
Data collection methods and measures for model variables

Variables	Methods	Measures
Water-based familiarity	Cognitive mapping recall	The extent to which water is in the first five features that come to mind when recalling the city or site as a two-dimensional map.
Water-based place identity	Photovoice recall	The extent to which water is in the first five pictures that people intend show to friends about a city or site.
Water-based comfort	Interview	The extent to which water helps people relax when they are stressed.
Water-based place dependence	Interview	The extent to which people use water to orient themselves in a city.
(Allocentric) aquaphilia	Emotional recall	The extent to which water is among the first five features people will miss about a city.

The author triangulated cognitive mapping (Quaiser-Pohl, Lehmann, & Eid, 2004), photovoice (Ruggeri, 2014), and non-visual recall protocols as semi-structured questions in an interview questionnaire to study people’s schemas of water cities as three types of representations: 1) two-dimensional (allocentric) structure (Marcouiller et al., 2004); 2) three-dimensional eye-level (egocentric) identity (Marcouiller et al., 2004); and 3) non-imageable meaning.

While key measurement protocols can be found in detail in Chapters II-V, the following section outlines some techniques the author employed to facilitate data integration across chapters. Participants frequently had difficulty drawing sketch maps by recalling cognitive maps from their spatial memories. As a result, before the investigator asked the participants to draw sketch maps, they were instructed to envision a particular city as a two-dimensional map and probe the recall sequence of the five most salient elements in their cognitive maps. Similarly, for the questionnaire-administered photovoice protocol, the investigator asked the participants to imagine taking five pictures to describe a particular city to their friends who had never been there. They were then instructed to describe five pictures that came to their mind sequentially before locating these five pictures on a map to show where they would have been standing to take each picture and the view shed associated with each picture. Each sketch map element or photovoice scene that emerged from their spatial memory was assigned a base score of one or zero depending upon whether or not it contained water. The order of the recall sequence was then used as a basis for weighting the base score for each element or scene to help account for its level of salience in spatial memory. The investigator took a weighted average of these base scores as a measure of water-based familiarity for the cognitive mapping results and as a measure of water-based place identity for the photovoice outcomes. As described in detail in other chapters, participants were also asked three more questions in order to obtain measures of non-imageable perceptions, which were water-based comfort, water-based place dependence, and allocentric aquaphilia as the structuralist influence of aquaphilia on topophilia. The participants were also asked to provide reasons behind their answers for these indicator questions. These answers are content-analyzed in Chapter II to help understand the influence of pictorial aquaphilia on urban design quality of water urbanism and to inform the aesthetic perceptions underlying functional measures identified for use in subsequent chapters.

CHAPTER II

WATER URBANISM:

THE INFLUENCES OF AQUAPHILIA ON URBAN DESIGN

Introduction

Aquaphilia as a Timeless Concept

Love for water is a timeless place-making concept that has received little attention in the empirical urban design literature. By reviving the origins of 'aqua' in Latin as water and 'philia' in Greek as love, aquaphilia is used to denote innate human affection towards water and water-centric environments. Historically, many flood-prone water cities, such as those in the Yellow River Basin of China (Yu, Lei, & Dihua, 2008) and Angkor Wat in Cambodia (Shannon & Manawadu, 2007), adopted a water-coherent approach in their public realm to create adaptive measures for floods and droughts. Such water urbanism was characterized by a systematic integration of waterscapes, including a large body of water within the city limit, a moat or lake along the city perimeters, or an interconnected network of canals, ponds and wetlands for flood retention, conveyance and groundwater recharge. Yet, most of these historic water cities have been popularly discussed only as tourist destinations, largely because the original hydrological functions of their waterscapes have often been forgotten or substantially lost (Yu et al., 2008).

From Biophilic Urbanism to Aquaphilic Urbanism

Whereas most contemporary cities do not have interconnected waterscapes, green infrastructure networks have been brought into the urban design discourse to encourage water retention as a way to better adapt cities to the increasing flood risks due to climate change impacts (Lennon, Scott, & O'Neill, 2014). This more water-coherent urbanism as a green infrastructure movement has been proposed by Beatley and Newman (2013) as a primary pathway through which biophilic urbanism contributes to climate change mitigation and adaptation. Such a climate-induced water-coherent impetus in biophilic urbanism may have helped engender an increasing number of stream daylighting projects (Beatley and Newman 2013). Although most of these stream daylighting projects are more linear than networked, this increasing water-coherent discourse as an emerging trend in biophilic urbanism suggests a possible return to an aquaphilic urbanism characteristic of many historic water cities. The pervasive appeal of historic water cities as popular tourist destinations suggests that aquaphilia has contributed to a favourable aesthetic perception of their urban design quality that has potentially motivated proximity-seeking behaviours, such as tourism.

Project Objective

This paper intends to initiate a dialogue around a potential theory of aquaphilic urbanism by qualitatively exploring the potential effects of aquaphilia on the perceived urban design quality of water urbanism. This dialogue may help to suggest possible future directions for quantitative research.

Literature Review

In Search of an Aesthetic Discourse for Green Infrastructure

The burgeoning discourse about green infrastructure has remained largely technical and included best management practices, low-impact design, sustainable urban drainage systems and water-sensitive urban design (Coombes, Argue, & Kuczera, 2000; Marsalek & Chocat, 2002). Although design professions have searched for an appropriate aesthetic for green infrastructure, the aesthetic performance of green infrastructure has received little attention in the design literature (Backhaus & Fryd, 2013).

The Effects of Water's Presence on Perception of Green Infrastructure

An evaluation of the aesthetic performance of twenty landscape-based storm water management projects in Northern Europe reveals that the frequent absence of water made these designs incoherent due to the lack of a strong connecting idea (Backhaus & Fryd, 2013). Whereas this study speculates that water may improve the aesthetics of green infrastructure by increasing its connectivity, the presence of water does not necessarily encourage proximity-seeking behaviours towards green infrastructure. One study discovered that the presence of water was not a significant predictor for the recreational use of undesignated open spaces along the urban and suburban stream corridors in Houston's Buffalo Bayou; instead, proximity to stream corridors, pedestrian access and tree cover were the best predictors (Shafer, Scott, Baker, & Winemiller, 2013). Whereas the presence of water could potentially help encourage people to visit the areas along the stream corridors, it is likely that this motivational influence of water may have been outcompeted by more powerful inhibitive factors affecting accessibility and comfort. Likewise, there has been little empirical investigation into how the presence of water interacts with urban design attributes to influence human affection or aversion towards accessible water networks found in historic water cities known as alluring tourist destinations.

Green Infrastructure as a Locus of Attachment Due to Comfort

An exploratory study investigates a similar system of green infrastructure as "greenery and open spaces linked by streets, waterways and drainage ways around and between urban areas” in an old town in central Peninsular Malaysia (Mansor & Said, 2008, p. 1). The findings show a strong attachment to green infrastructure among most of the 335 residents surveyed due to the affordance of green infrastructure for relaxation and stress reduction. Similar to the Houston study, comfort appears to be an influential attribute associated with most residents’ frequent use of the green infrastructure’s open spaces.

Green Infrastructure as a Spatial Anchor and Contributor to Attachment

The findings from the survey conducted in the Malaysian old town also suggest that the attachment to green infrastructure contributes to the attachment to the town through its diversity, coherence and naturalness. The study defines diversity as “experiential choices for urban residents”, naturalness as “the presence of lush greenery and water element that attract residents to participate” and coherence as a composite concept of legibility, connectivity and accessibility that facilitates the “wayfinding and orientation of residents” (Mansor & Said, 2008, p. 3). This definition of coherence seems to refer to the extent to which green infrastructure functions as a spatial anchor, that is, a salient feature that contributes to the coherence of environmental image to aid orientation (Marquardt & Schmieg, 2009; Park, Puglisi, & Lutz, 1982).

The Affordances of Green Infrastructure as a Locus of Attachment

According to the prospect-refuge theory (Appleton, 1975), diversity and coherence as a composite concept of legibility, connectivity and accessibility seem to be associated with prospect and escape based on the following speculations: legibility and visual connectivity are similar to prospect, whereas physical connectivity and accessibility are related to escape. Diversity (of experiential choices) may contribute to prospect through balancing visual connectivity with complexity to increase legibility. Diversity may also influence refuge by increasing complexity to generate more eyes on the street. Naturalness seems to relate to aquaphilia and biophilia as instinctual human attachment to water and living organisms. Both aquaphilia and biophilia may contribute to stress reduction and increase comfort as a possible correlate of refuge. The findings from the study support the speculation that residents' attachments to their town may be attributed to the affordances of a green infrastructure network for prospect and escape as a spatial anchor and for refuge through aquaphilia and biophilia. However, it is unclear how the presence of water interacts with certain urban design attributes associated with green infrastructure's affordances to influence residents' attachments to the green infrastructure and the town. In fact, coherence as legible connectivity has been identified as a desirable aesthetic quality of green infrastructure associated with the presence of water (Backhaus & Fryd, 2013). This finding indicates that the presence of water may contribute to certain urban design attributes essential to the functioning of green infrastructure as a locus of attachment or a spatial anchor that enhances residents' attachments to their town or city.

Coherence as an Urban Picturesque Concept

Coherence refers to physical connectivity and visual continuity for unifying distinct parts (Backhaus & Fryd, 2013) or a range of urban design attributes, such as legibility, connectivity and accessibility (Mansor & Said, 2008). These definitions are similar to the notion of coherence that juxtaposes the 'identity' of urban scenes and their connections as complexity and unity. The ostensible duality in these descriptions of coherence is harmonized under the premise that associations can be more readily made among identifiable, rather than undifferentiated, urban landscape forms (Lynch, 1990).

Pictorial Coherence

Coherence as a dualistic concept of complexity and order can be traced back to the origin of the urban picturesque tradition in the ‘street picture’, a term popularized by Unwin (1908, 1914). The author coins pictorial coherence to allude to both the static eye-level perspective and the good urbanistic composition found in the street picture as an identifiable scene (Raynsford, 2011). The street picture provides “a stable set of spatial co-ordinates for the viewer, establishing scales and distances between the viewing subject the perceived urban space” (Raynsford, 2011, p. 48). The contrast and variety the picture produces also enables “the eye to rest on prominent objects and the mind to make associations among contrasting elements” (Raynsford, 2011, p. 48). These prominent objects provide a pattern of continual guidance to connect one contrasting element with another to evoke aesthetic experiences (Beardsley, 1958; Isaacs, 2000). The intensity of such aesthetic experiences increases with a higher degree of complexity and decreases after it peaks at an optimal level (Berlyne, 1974).

Egocentric Coherence

The author proposes the term egocentric coherence to refer to a visually captivating sequence of street pictures as recognizable urban scenes and their connections based on a dynamic eye-level perspective. This cinematic analogy characterizes the work of many urban picturesque theorists as follows (Isaacs, 2000; Raynsford, 2011): Unwin’s (1909) curved road proposal for generating a series of ever-changing street pictures; Sitte’s (1945) artistic theory for arranging streets; and Cullen’s (1971) townscape movement for the use of architecture to visually anchor a sequence of views to discourage visual attention from scattering.

Allocentric Coherence

The author proposes the term allocentric coherence to emphasize the two-dimensional map-like frame of reference, introduced by Lynch's (1960) notion of imageability, to the urban picturesque discourse of the pictorial as a kind of egocentric coherence. Unlike the eye-level perspectives associated with pictorial and egocentric coherence, the allocentric reference frame is based on the external environment and is independent of an observer's location. Imageability describes the urban design attribute of an environment that evokes a strong image to generate a sense of identity as a gestalt greater than a legible environment composed of the sum of map-able patterns and identifiable scenes (Lynch, 1960). Similar to egocentric coherence, imageability as allocentric coherence seems to be a dual-view concept involving a strong two-dimensional image as a unified pattern of allocentric mappability and pictorial identifiability. Although egocentric coherence refers to the continuity of connections between identifiable scenes, such connections are not necessarily map-able two-dimensional configurations. Lynch's (1960) theory of imageability for public city image has mainly focused on integrating structure and identity as two distinctive concepts based on two different perspectives because meaning, the third component of imageability, tends to be individually differentiated.

Emotional Coherence

Emotional coherence describes the emotional security underlying a sense of orientation resulting from interactions with an imageable environment that facilitates psychological integration (Raynsford, 2011). Based on the definition of coherence as legibility, accessibility and connectivity, the coherence of green infrastructure as a spatial anchor has been found to contribute to people's town attachments (Mansor & Said, 2008). These observations suggest that certain urban design attributes of spatial anchors may contribute to emotional coherence with a city through the attributes' influences on the city's imageability.

Research Design

Site Selection

Imageability has been speculated as a likely urban design quality associated with water-centric cities, such as Venice and Dutch polder cities (Lynch, 1960). This study selected six water cities, each known as 'the Venice of the North', including Amsterdam and Giethoorn in the Netherlands, Hamburg and Berlin in Germany and Bruges and Ghent in Belgium and the two fastest growing Dutch polder cities of Almere and Rotterdam to investigate the influence of aquaphilia on the aesthetic coherence of water-centric cities. These eight potentially imageable cities were chosen because of their similar precipitation patterns and geographic proximity, which minimizes sampling costs.

Data Collection

Sixty participants were conveniently sampled from these eight water cities for semi-structure interviews. Similar to Lynch's (1960) methods in *The Image of the City*, each interview engaged a participant to recall his or her urban environment as a cognitive map and a series of eye-level snapshots in addition to answering questions. In the cognitive mapping protocol, the investigator asked participants to imagine drawing a map of the city from which they were sampled and name or describe the five features or locations that came to mind first. Then, in the photovoice protocol, participants were guided to describe the contents of five pictures they would take of the city to describe it to someone who had never been there. Participants also had to provide a reason for recalling each cognitive mapping and photovoice feature. Finally, the participants were asked to point out three likes and dislikes about the city's existing water networks. This question was last so that the reference to water would not affect participants' answers to the earlier questions that did not mention water.

Analytical Framework

Descriptors of Urban Design Quality

To synthesize the inconsistent definitions of various nuanced urban design attributes in the literature into evaluative criteria, the author generated Table 2.1. with definitions for nine urban design quality descriptors derived from the use of 'urban design' as search-key words. Some urban design theorists refer to coherence as a sense of visual order derived from harmonious interrelationships among physical elements (Ewing, Handy, Brownson, Clemente, & Winston, 2006). This term was replaced with 'order' in Table 2.1. to distinguish it from coherence as a dualistic concept in the urban picturesque tradition. Although imageability could be dominated by either allocentric mappability or pictorial identifiability, it was included in Table 2.1. as a perspective independent attribute. Imageability was only differentiated as mappability and identifiability for analyzing the results of cognitive mapping and photovoice protocols, respectively.

Urban Design Attributes Based on Affordance Types

Table 2.2. classifies these urban design attributes based on prospect, refuge and access according to the following assumptions: Access is a more appropriate concept than escape for referring to the ability to navigate to and between destinations easily in contemporary cities because the prospect-refuge theory alludes to escape in the sense of eluding predators as threats.

Table 2.1. Definitions of urban design quality descriptors**.**

Quality	Definition	Source
Imageability	A coherent structure of physical arrangements or elements that evoke a strong image and identity.	(Lynch 1960; Ewing et al. 2006)
Legibility	A recognizable pattern of high continuity with identifiable features that facilitate orientation.	(Lynch 1960; Ewing et al. 2006)
Order	A sense of visual order derived from harmonious interrelationships among all physical elements.	(Ewing et al. 2006)
Connectivity	Visual or physical connections between physical elements are continuous.	(Ewing et al. 2006; Mansor and Said 2008)
Accessibility	Proximity and affordance of access.	(Mansor and Said 2008)
Openness	The volume of space measured from all possible observation points.	(Fisher-Gewirtzman & Wagner, 2003)
Transparency	The degree to which people can see physical elements and human activities beyond an edge.	(Ewing et al. 2006)
Complexity	Visual richness from a fine-grained mix of diverse activities, experiences and forms.	(Ewing et al. 2006)
Comfort	The result of elements that enhance wellbeing and reduce stress.	(Mansor and Said 2008)

Table 2.2. Urban design attributes and affordance types.

Affordance	Urban Design Attributes
Prospect	Openness/transparency/imageability/legibility/order
Refuge	Complexity/comfort
Access	Connectivity/accessibility

Both connectivity and accessibility are potential correlates of access to account for the continuity of linkages, the proximity of destinations and the ease of physical access (Ewing et al., 2006; Mansor & Said, 2008). Since prospect involves the human capacity to see, it may be related to openness, transparency, order, imageability and legibility (Appleton, 1975; Dosen & Ostwald, 2013). Comfort and complexity may have affinities with refuge because they imply relaxation in a secluded environment without being seen or a safe environment with eyes on the street (Appleton, 1975; Dosen & Ostwald, 2013).

Data Analysis for Likes and Dislikes about Water Networks

Recall Sequence as an Emotional Salience Indicator

Participants' reasons for likes and dislikes of the existing water networks were ranked on a scale from 3 to 1, according to the sequence in which they were recalled, to indicate their relative levels of emotional salience in recall memory. The author grouped these reasons into response categories using participants' original wordings as much as possible before classifying the response categories based on the descriptors in Table 2.1. to derive a weighted frequency total (WFT) for each descriptor. As these WFTs were not intended as variables for quantitative research, their inter-rater reliabilities were not tested. Instead, these WFTs were used to gauge the relative contributions of various urban design attributes to the participants' likes and dislikes about the existing water networks to inform future quantitative research. The response categories generated from the original wordings of participants' reasons were presented with their WFTs so readers could judge whether the proposed classifications were appropriate. Two other researchers reviewed the classification results. Some response categories were classified under aquaphilia or biophilia because they did not appear to fit in any urban design descriptors from Table 2.1. and seemed to relate to love for water or nature. The author cross-referenced the urban design descriptors in Table 2.1. with prospect, refuge and access in Table 2.2. to generate bar charts of WFTs based on both urban design attributes and affordances.

Results and Discussions for Likes and Dislikes about Water Networks

Urban Design Attributes as Contributors to Likes and Dislikes

As shown in Table 2.3., accessibility received the highest WFT (WFT = 47), followed by aquaphilia (WFT = 42) and complexity (WFT = 42), comfort (WFT = 29), legibility (WFT = 17), openness (WFT = 8), connectivity (WFT = 8), imageability (WFT = 7), order (WFT = 4), biophilia (WFT = 3) and transparency (WFT = 1). In contrast, participants' aversions to the existing water networks seemed more affected by threats to aquaphilia (WFT = 72) than the potentially influential urban design attributes of accessibility (WFT = 28), complexity (WFT = 27), connectivity (WFT = 18), biophilia (WFT = 3), legibility (WFT = 2) and transparency (WFT = 1). Compared with other urban design attributes, these potential contributors to participants' dislikes about the existing water networks may be more vulnerable to structural factors, such as the presence of locks and tall reeds as physical and visual barriers.

Table 2.3. Reasons for likes and dislikes about water networks.

Attribute	WFT	Categories of Reasons for Likes (WFT) and Dislikes (WFT)
Imageability	7	**Likes:** provides city identity (3); unique (3); iconic (1)
Order	4	**Likes:** organizes the city with openness vs. density (2); lack of water transportation makes inner-city waterways more integrated with the cityscape (2)
Connectivity	8	**Likes:** they are connected (3); we are linked to the world through the water network (2); ports for world trade (3)
	13	**Dislikes:** more bridges are needed (1); lack of a loop (3); some locks are closed during off-peak times (2); not part of the transportation system (1); not a network because separate waters are connected by pipes or locks (6)
Legibility	17	**Likes:** provides orientation (3); well-defined edges (2); gives reasons for bridges as spatial markers (8); it makes wayfinding easy (1); people describe their locations as being close to different bodies of water (3)
	2	**Dislikes:** they look the same (2)
Complexity	42	**Likes:** provides a variety of sights (3); everything is built along the waterways (1); spectacular lighting for waterfront buildings (3); nice to watch people (4); fun (2); tourist attractions (9); used for sports and recreation (20)
	27	**Dislikes:** more waterfront programming is needed (2); too busy with boats and tourists (18); does not offer a lot of

		opportunities (2); commercial boats create visual clutters (5)
Comfort	29	**Likes:** helps me relax (11); cosy (2); exclusive (1); quaintness (3); silence (5); peaceful (1); meditation (3); makes hot summer enjoyable (2); creates a comfortable microclimate (1)
Accessibility	47	**Likes:** saving commute time with ferries (6); access to water transportation (29); nice to walk around (3); extensive (1); omnipresent (8)
	28	**Dislikes:** no regular schedule for water transportation (3); water transportation is for tours only (1); opening the bridges for commercial boats makes suburban commuters wait for a long time (4); hampered land transportation (2); less space for more convenient things (1); no water transportation (3); rent rises because of proximity to water (2); expensive boat tours (3); having to bike on steep slopes up to bridges (3); canals make it hard to reach some houses without a boat (3); river separates the city (3)
Transparency	1	**Likes:** I like the way water separates houses to provide privacy for neighbours living close together without fences (1)
	1	**Dislikes:** tall reeds cause visibility issues (1)
Openness	8	**Likes:** openness (6); panorama of the landscape (2)
Aquaphilia	42	**Likes:** beautiful water (21); clean water (3); picturesque view

		with water (3); reflection of light on water; (1) nice and still water (1); good views with water (7); water creates nice atmosphere (3); water doesn't smell (3)
	77	**Dislikes:** mosquitoes (11); smoke from boat exhaust pipes (1); rats (3); trash in water (5); keep-the-canal-clean tax is not being well used (1); smell (13); too noisy (3); not very clean (19); not enough movement to keep water clean (5); no rescue if I fall into the water (2); not swimmable (1); algae growth (6); possibility of flood when it rains a lot (2); too much water (1); not enough water (4)
Biophilia	3	**Likes:** beautiful nature (2); water birds (1)
	3	**Dislikes:** not enough green along water (3)

Negative Influence from the Threats to Pictorial Aquaphilia

Among reasons underlying participants' fondness for the existing water networks, those classified under aquaphilia seemed to be mostly associated with instinctual human affection towards clean and safe water, as perceived from a static eye-level perceptive. As shown in Table 2.3., pictorial aquaphilia received the second highest WFT. This result suggests that the contribution of pictorial aquaphilia to participants' preferences for the existing water networks may need to be controlled in future quantitative research to better understand the influences of urban design attributes. Concurrently, threats to pictorial aquaphilia (WFT = 71) seemed to be a more important contributor than the positive influence of accessibility (WFT = 47) to the public perception of existing water networks.

The negative influence of pictorial aquaphilia also seemed to be a stronger factor than poor accessibility (WFT = 28) in explaining people's dislikes about the existing water network. Whereas the presence of clean and safe water and accessibility may help motivate emotional coherence with water networks, the sight of unclean and unsafe water could potentially be a more powerful inhibitive force. The threats to pictorial aquaphilia could possibly explain water-resistant urbanism, which is characterized by an avoidant mindset stemming from a dominant desire to remove potentially harmful water sources from the city.

Intrinsic Urban Design Quality of Egocentric Aquaphilia

Openness, order, imageability and comfort were the four urban design attributes not influenced by dislikes. These attributes might be less vulnerable to structural factors and, thus, potentially useful urban design attributes that realize egocentric aquaphilia due to emotional coherence with water networks. As shown in Figure 2.1., pictorial aquaphilia seemed to positively influence egocentric aquaphilia through access and refuge more than prospect. The negative influences on egocentric aquaphilia seemed to originate mostly from refuge, followed by access and prospect. Prospect could potentially be an inherent affordance of egocentric aquaphilia because of its negligible contributions to the dislikes of the existing water networks. In fact, among the four inherent urban design attributes of water networks identified in the last section, openness, order and imageability can reasonably be assumed potentially associated with prospect.

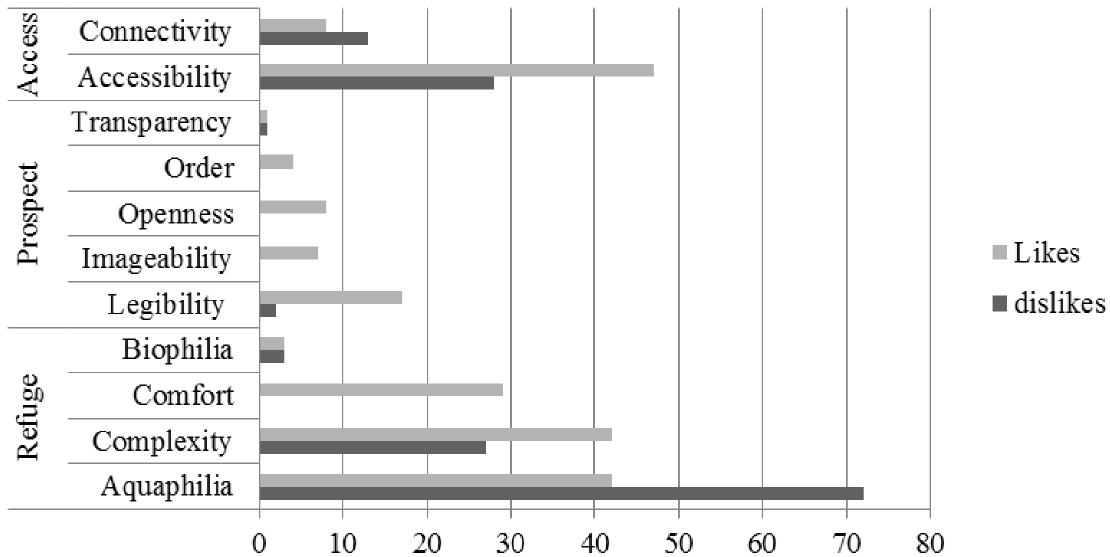


Figure 2.1. Weighted frequency totals (WFTs) of urban design descriptors associated with likes and dislikes about the existing water networks.

However, the low WFTs of openness, coherence, imageability and legibility could possibly support one of the following two alternative interpretations: These urban design attributes of prospect could potentially require the use of visual recall methods, such as cognitive mapping and photovoice, or these attributes associated with prospect might be the least relevant to egocentric aquaphilia because they seem to be associated with either pictorial or allocentric coherence.

Data Analysis for Cognitive Mapping and Photovoice

Waterscape Types Based on Elements of Imageability

Lynch's (1960) five elements of imageability, including path, landmark, node, edge and district, were used to categorize all water features into five waterscape types: canals (water-based paths), water landmarks (water-based landmarks), lakes (water-based nodes), rivers (water-based edges) and harbours (water-based districts). The basis for this classification was on whether these terms were part of the participants' answers or the actual names of these waterscapes. Water landmarks refer to salient features along or across water, such as canal houses, boathouses or bridges.

Recall Sequence as an Indicator of Spatial Anchor Salience

According to the anchorpoint theory (Golledge, 1984), higher-order spatial anchors tend to be recollected first and surrounded by clusters of lower-order spatial anchors emerging sequentially as a hierarchy of proximities in people's cognitive maps. Thus, the responses for cognitive mapping and photovoice recall protocols were ranked from 5 to 1 to reflect the sequence in which they arose in each participant's spatial memory from the first to the last. These weighted frequencies were used to indicate the extent to which each feature functioned as a spatial anchor, that is, a salient feature that aids wayfinding (Marquardt & Schmieg, 2009; Park et al., 1982).

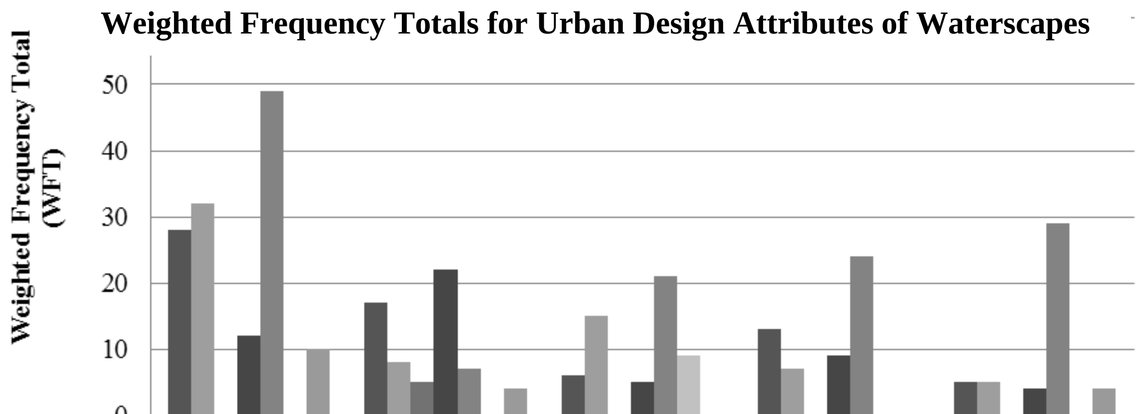
Urban Design Attributes as Contributors to Waterscape Salience

Each reason for recalling a waterscape was consolidated into response categories, which were then classified by the author using the urban design attributes from Table 2.1. to generate WFTs by waterscape types. Imageability was replaced by mappability for cataloguing cognitive mapping and by identifiability for photovoice results to capture the nuances of imageability in allocentric and egocentric frames of reference.

Results and Discussions for Cognitive Mapping

Contribution of Imageability to Waterscape Allocentric Salience

As in shown in Figure 2.2. and Table 2.4., with the exception of lakes, imageability seemed to be the most common reason underlying the allocentric salience of canals as spatial anchors (WFT = 49), followed by rivers (WFT = 21), harbours (WFT = 24) and water landmarks (WFT = 29). In contrast, imageability (WFT = 7) was only the fourth most frequently mentioned urban design attribute for lakes after complexity (WFT = 22), aquaphilia (WFT = 17) and accessibility (WFT = 8). For each waterscape type in Figure 2.2., the WFTs for urban design attributes are presented from top to bottom in each column for the table and from left to right for the bar chart.



	Canals	Lakes	Rivers	Harbours	Water Landmarks
Aquaphilia	28	17	6	13	5
Accessibility	32	8	15	7	5
Comfort	0	5	0	0	0
Complexity	12	22	5	9	4
Imageability	49	7	21	24	29
Legibility	0	0	9	0	0
Meaning	10	4	0	0	4

Figure 2.2. Weighted frequency totals (WFTs) of urban design descriptors associated with reasons for recalling five waterscape types during cognitive mapping protocol.

Table 2.4. Cognitive mapping weighted frequency totals (WFT) for waterscapes.

Quality	WFT	Categories of reasons for recall waterscapes (WFT)
132 Canals (water paths) (WFT)		
Imageability (mappability)	49	Characteristic of Amsterdam (5); unique (5); gives a distinct shape to the city (5); characteristic part on a map (5); recognizable and symbolic (8); they structure the city (3); I have seen them on the map (2); defines the shape of the city (17)
Accessibility	32	That is where the boat tour starts (5); close to where I work (5); the boat tour down the canals helped me learn about the city (5); they are everywhere (9); in the middle of the city centre (4); tourist boats (4)
Aquaphilia	28	Nice because they have water (5); I like it (17); the effects of water look good (1); I am water-minded (5); scenic and stuck in my head (1)
Complexity	12	It brings life (5); all life happens along the canal (5); tourist attraction (2)
Meaning	10	That's where I put my boat (1); that's why the city was called mini-Venice (4); the city is famous for its waterways (5)
63 Lakes (water nodes) (WFT)		
Complexity	22	Lots of activities around (5); it's the city's number one attraction (15); that's where people play football (2)

Aquaphilia	17	They are beautiful (4); I like it (13)
Accessibility	8	It’s in the centre of the city (7); they are everywhere (1)
Imageability (mappability)	7	Major part of the city image (2); it defines the city centre (5)
Comfort	5	Quiet because water absorbs ambient noises (5)
Meaning	4	Romantic place (4)
55 Rivers (water edges) (WFT)		
Imageability (mappability)	21	Recognizable shape in the city (7); it’s a salient feature on the map (5); important for the city (4); it defines the shape of the city (4); part of the city image (1)
Accessibility	15	It’s everywhere; you cannot miss it (5); goes through the city centre and is part of the city (5); I have been on a boat tour (5)
Legibility	9	Gives orientation (4); organizes the city aerial view (5)
Aquaphilia	6	The city was built along the river (5); nice to sit by water (1)
Complexity	5	Busy with activities and people (5)
53 Harbours (water districts) (WFT)		
Imageability (mappability)	24	Biggest element of the city large water body (5); it’s a large body of water and thus very visible on a map (3); it’s big (12); it defines the northern edge of the city (4)
Aquaphilia	13	Beautiful open water (4); I like it (4); places with views of water (4)

Accessibility	7	Ferries to the other side of town; (2); brings people to our city (5)
Complexity	9	Touristy with ships (4)
47 Water landmarks (WFT)		
Imageability (identifiability)	29	Canal houses (5): I have seen people taking pictures of canal houses (3); recall seeing canal houses during a boat tour (7) Boathouses (4): remember seeing boathouses during a boat tour (4) Bridges (19): iconic (10); visual quality (5); popular (4)
Accessibility	5	Bridges (5): they are everywhere (5)
Aquaphilia	5	Bridges (5): I like it (5)
Complexity	4	Bridges (4): tourist attraction (4)
Meaning	4	It has personal meaning because I used to live around there (4)

Dual-View Nature of Spatial Knowledge in Cognitive Maps

The response categories classified under imageability for canals and rivers seemed to describe the extent to which these two waterscape types were map-able as a recognizable two-dimensional configuration. However, those categories classified under imageability for water landmarks seemed to refer to the degree to which their forms were memorable as a pictorial visual quality. The findings potentially indicate the dual-view nature of spatial knowledge recalled from an allocentric cognitive image.

Waterscape Imageability and Urban Design Implications

The imageability related to harbours seemed to be associated with their large sizes and resultant visibility on a map, creating extent-based mappability. The imageability of lakes could potentially be related to their central locations in cities, serving as a type of location-based mappability. Whereas harbours and rivers cannot be easily created, retrofitting cities with map-able canals and identifiable bridges and waterfront features could possibly help increase the imageability of these elements. Furthermore, whereas incorporating centrally located lakes into new towns could possibly help increase the lakes' imageability, it might be more effective to focus on making lakefront edges more vibrant through programming and designing because complexity was a more frequently mentioned reason than the location-based imageability was for recalling lakes.

Aquaphilia's Influence on Allocentric Salience of Waterscapes

Aquaphilia was the second most frequently mentioned reason for recalling both lakes (WFT = 17) and harbours (WFT = 13). Aquaphilia (WFT = 28) was almost as frequently stated as accessibility (WFT = 32) as a reason for recalling canals. Pictorial aquaphilia was likely to have undeniable influences on the imageability of water-centric cities through its contribution to the salience of lakes, harbours and canals in cognitive maps. Given the greater presence of lakes and harbours in coastal than inland cities, systematic integration of canals with urban fabrics might be one possible way to help increase the imageability of inland cities by using aquaphilia to influence the salience of canals in cognitive maps.

Accessibility's Influence on Allocentric Salience of Waterscapes

Accessibility was the second most frequently mentioned reason for recalling canals (WFT = 32), rivers (WFT = 15) and water landmarks (WFT = 5). As shown in Table 2.4., accessibility captured the notions of proximity and easy physical access related to a waterscape's location, extent, coverage and density in a city. These distributional factors of waterscapes could potentially have implications on the waterscapes' salience in cognitive maps.

Canals, Rivers, Lakes and Harbours as Distinct Waterscape Types

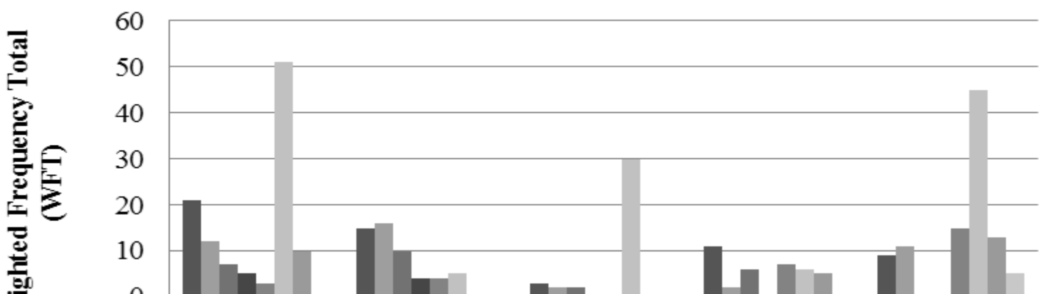
Canals, rivers, lakes and harbours should be considered distinct waterscape types for future quantitative research. As shown in Table 2.4., the most common reason for recalling lakes as water nodes seemed to be related to complexity. In contrast, harbours as water districts were recalled mostly because of their size-based imageability. By removing legibility, imageability seemed to be the most common reason for recalling both canals and rivers, followed by accessibility, aquaphilia and complexity. Legibility seemed to distinguish rivers from canals as a distinct waterscape type. For example, participants recalled a river because "it gave orientation" or "organized the city aerial view", whereas the reasons for recalling canals tended to be related to the distinct shape they formed. One postulate could be that the greater lengths and widths of rivers create more spatial references than canals create. On the contrary, Jonge (1962) believed the concentric rings of canals in Amsterdam might provide a greater sense of direction due to their multiple bends with more pronounced curvatures. Given the tendency of rivers to have single-district edges with minimal curvatures, this perspective could potentially suggest that canals with map-able configurations or pronounced curvatures might be more legible than rivers. Future research may investigate the impacts of length, width and curvature on the legibility and imageability of linear waterscapes.

Results and Discussions for Photovoice

Pictorial Coherence of Canals, Rivers and Water Landmarks

For each waterscape type listed in Figure 2.3., the WFTs for urban design attributes are presented from top to bottom in each column for the table and from left to right for the bar chart. As shown in Table 2.5., imageability explained most of the reasons for recalling canals (WFT = 51), rivers (WFT = 30) and water landmarks (45) during the photovoice protocol.

Weighted Frequency Totals for Urban Design Attributes of Waterscapes



	Canals	Lakes	Rivers	Harbours	Water Landmarks
Aquaphilia	21	15	3	11	9
Accessibility	12	16	2	2	11
Biophilia	7	10	2	6	0
Comfort	5	4	0	0	0
Complexity	3	4	0	7	15
Imageability	51	5	30	6	45
Meaning	10	0	0	5	13
Openness	0	0	0	0	5

Figure 2.3. Weighted frequency totals (WFTs) of urban design descriptors associated with reasons for recalling five waterscape types during photovoice protocol.

Table 2.5. Photovoice weighted frequency totals (WFT) for waterscapes.

Quality	WFT	Reasons for recall waterscapes (WFT)
109 Canals (water paths) (WFT)		
Imageability (identifiability)	51	Great view of the cityscape across water (20); very characteristic wherever you go (12); the view makes you feel like being in Venice (8); picturesque landmarks that attract people (4); canals with multiple bridges create good compositions (7)
Aquaphilia	21	Presence of water (4); beautiful sight of water (12); clean water (5)
Accessibility	12	You see them during the boat tour (3); because you have to cross it (5); you can take a trip on a boat (3); nice to walk around them (1)
Meaning	10	Famous postcard shots typically cover the canals (10)
Biophilia	7	Presence of vegetation (4); you can watch animals (3)
Comfort	5	It's quiet (5)
Complexity	3	You can watch boats (3)
54 Lakes (water nodes) (weight)		
Accessibility	16	It's in the centre of the city (9); to swim at the beach (4); typical (3)
Imageability (identifiability)	5	Picturesque views of the city across the lake (5)
Aquaphilia	15	Presence of water (5); I like this lake (5); beautiful lake (5)

Biophilia	10	Presence of vegetation (7); I like how it is in a park (3)
Complexity	4	You can watch boats (4)
Comfort	4	It's quiet (4)
37 Rivers (water edges) (weight)		
Imageability (identifiability)	30	Great view with an overall sense of the cityscape across the river (19); scenic view with bridges (10); great views of the big river with houseboats and historic bridges (1)
Aquaphilia	3	I like water (3)
Accessibility	2	The river is everywhere (2)
Biophilia	2	Nature (2)
82 Harbours (water districts) (weight)		
Aquaphilia	11	Presence of water (6); large amount of water makes it special as they are often too many boats in lakes (5)
Complexity	7	You can watch ships and tourists (7)
Imageability	6	Unique views of the skyline across the water (6)
Biophilia	6	Presence of vegetation (6)
Meaning	5	Historic significance (5)
Accessibility	2	Access to water transportation (2)
98 Water landmarks (weight)		
Imageability (identifiability)	45	Beautiful views (28); special views of the skyline and bridges across the water (12); recognizable bridge (5)
Complexity	15	I like watching sail boats (3); variety of bridges (2)
Meaning	13	Famous (7); it connects two cities symbolically (4); my

		boats (2)
Accessibility	11	Typical (10); nice boats for tourist trips (1)
Aquaphilia	9	Scenic view with water (9)
Openness	5	Openness created by water allows views to the skyline (5)

Aquaphilia's Influence on Egocentric Coherence of Water Cities

Aquaphilia was the most frequently mentioned reason for recalling harbours (WFT = 11) and second most frequent reason for recalling lakes (WFT = 15) and canals (WFT = 21). Aquaphilia (WFT = 15) was almost as frequently stated as accessibility (WFT = 16) as a reason for recalling lakes. Pictorial aquaphilia as instinctual human attachment to clean and safe water scenes was likely to have incontestable influences on the pictorial coherence of lakes and harbours and their salience as identifiable scenes. In contrast, imageability was a more frequently declared reason than aquaphilia for recalling canals, rivers and water landmarks as scenes. Participants' wordings showed that these imageable scenes were more likely to contain both types of linear waterscape as visual anchors connecting water landmarks with visual interests. The contrast between anchoring and differentiating features possibly made these scenes more identifiable than aquaphilic pictures of clean and safe water scenes in the case of lakes and harbours. Whereas lakes and harbours are more prevalent in coastal than inland cities, introducing canals as continual patterns of guidance through areas with recognizable features may help increase the imageability of inland cities.

Accessibility's Influence on Egocentric Coherence of Water Cities

Accessibility was the most frequently stated reason for recalling lakes (WFT = 16), the third reason for recalling canals (WFT = 12) and the fourth reason for recalling water landmarks (WFT = 11). This factor was barely mentioned for both rivers (WFT = 2) and harbours (WFT = 2). The findings could potentially suggest the proximity and ease of access due to the lakes' central locations. In contrast, for canals and water landmarks, these factors were not as important as pictorial coherence in influencing the salience of these systems in cognitive images. For rivers and lakes, these factors might have negligible influences, or rivers and lakes were simply not easily accessible or actively used.

Conclusions

Water-Based Comfort for Modelling Allocentric Aquaphilia

As shown in Table 2.6., comfort seemed to be a consistent contributor to people's emotional coherence with the water or green infrastructure networks and could potentially be a promising indicator of refuge. However, comfort was rarely mentioned as a reason for recalling waterscapes in the cognitive mapping and photovoice protocols. It is likely that comfort contributed primarily to the salience of waterscapes as a spatial anchor through its influence on people's attachments to and proximity-seeking behaviours towards waterscapes. For modelling allocentric aquaphilia as contributors to water-based spatial anchors of emotional coherence with water-centric cities, future research should use interview questions to capture water-based comfort as a potential construct. Water-based comfort could also potentially be used as a pictorial aquaphilia sensitivity baseline to account for its influences on allocentric aquaphilia.

Table 2.6. Comparison of influences on emotional coherence with green infrastructure.

Possible contributors to likes about the existing water networks: Accessibility (47), complexity (42), aquaphilia (42) and comfort (29)
Possible contributors to dislikes about the existing water networks: Threats to aquaphilia (77), accessibility (28), complexity (27) and connectivity (13)
Contributors to proximity-seeking towards green infrastructure (Shafer et al., 2013): Accessibility (proximity and pedestrian access)/comfort (tree cover)
Contributors to attachment to green infrastructure (Mansor and Said 2008): Comfort (relaxation and stress reduction)
Contributors to town attachment (Mansor and Said 2008): Complexity (diversity)/aquaphilia/biophilia/legibility/accessibility/connectivity

Water-Based Mappability and Identifiability for Modelling Allocentric Aquaphilia

Prospect might be measured by water-based mappability and identifiability as the allocentric and pictorial salience of waterscapes in environmental images. As shown in Figures 2.2. and 2.3., the allocentric and pictorial salience of canals, rivers, lakes and harbours as spatial anchors seemed to be mostly influenced by imageability, aquaphilia, accessibility and complexity. As indicated by Tables 2.4. and 2.5., participants' recall reasons classified under imageability seemed to imply a juxtaposition of connectivity and complexity. This finding suggests that cognitive mapping and photovoice recall protocols captured most of the urban design attributes of green infrastructure identified by Mansor and Said (2008) as possible contributors to town attachment.

Water-Based Orientation for Modelling Allocentric Aquaphilia

Whereas legibility was rarely a recall reason for cognitive mapping and photovoice protocols, many of the reasons for imageability implied some level of legibility. In addition, legibility was a rather intrinsic attribute associated with people's likes about water networks. Future research should use interview questions to measure water-based orientation as one of the constructs for modelling allocentric aquaphilia. Water-based orientation could potentially be a more promising indicator of access than connectivity and accessibility. Whereas legibility received almost no WFTs, both connectivity and accessibility received mid-range WFTs as reasons for dislikes about water networks. This finding revealed the vulnerability of connectivity and accessibility to structural factors, including the presence of tall reed grasses and locks.

Emotional Recall Protocol for Water-Based Emotional Coherence

Instead of investigating what people like or dislike about existing water networks, future research should use an interview question to capture the emotional salience of waterscapes in people's recall memory as water-based emotional coherence. Water-based emotional coherence can serve as an outcome variable for testing allocentric aquaphilia as a path analysis model of water-based mappability, water-based identifiability, water-based comfort and water-based orientation as four interrelated yet distinct constructs.

Effects of Waterscape Mappability, Identifiability and Attachment on Coherence

The WFTs of recall reasons based on urban design attributes only allowed a cursory comparison of the relative importance of urban design attributes to each waterscape type's contribution to their allocentric and pictorial salience as the structure and identity components of imageability. Future research may consider collecting and evaluating sketch maps to create two measures: allocentric coherence as the extent to which components of imageability form a coherent pattern to evoke a strong image and egocentric coherence as the degree to which sketch map features cluster along waterscapes to form continuous edges. Each coherence measure can serve as a dependent variable to study the contributions of mappability, identifiability and attachment of five waterscape types as independent variables. These independent variables can be generated from their sequence of recall to indicate each waterscape type's allocentric, pictorial and emotional saliencies as spatial anchors. Because some of the reasons for recalling water landmarks in cognitive maps were pictorial in nature, both allocentric and pictorial saliencies of waterscapes as independent variables should be included to allow this overlapping effect to be properly controlled. Similarly, pictorial aquaphilia contributed to the allocentric and pictorial salience of waterscapes, whereas several urban design attributes had influences on egocentric aquaphilia as attachment to water-based spatial anchors and allocentric aquaphilia as emotional coherence with water-centric cities. Including waterscape attachment could help account for the overlapping effect of all three types of aquaphilia with allocentric and egocentric saliencies.

Towards a Theory of Aquaphilic Urbanism

Lynch (1960) postulated that people's emotional coherence with their city was associated with its imageability, and imageability was a likely urban design quality associated with water-centric cities. His speculations suggested that the presence of water could potentially help increase the aesthetic coherence and other urban design attributes of an accessible water network. In addition, such a water network could potentially contribute to allocentric aquaphilia as a developed emotional bond with a water-centric city by improving its imageability. This exploratory study provided possible directions for substantiating this hypothesized relationship between water-based aesthetic coherence and emotional coherence for the best design of water networks to produce water-centric cities that contribute to quality of life. Aquaphilic urbanism as an aesthetic discourse may help adapt individuals and cities to a designed water-coherent urbanism, where interconnected green infrastructure systems are systematically integrated within urban fabrics to better address human needs and climate change impacts.

CHAPTER III

THE IMAGE OF THE WATER CITY: TESTING THE IMAGEABILITY THEORY FOR STRUCTURING THE PLURALISTIC WATER CITY

1. Introduction

1.1. Background

1.1.1. Imageability Due to Spatial Composition

In *The Image of the City*, Lynch (1960, p. 13) speculated that Venice and Dutch polder cites are probably imageable environments; specifically, he pointed out that Dutch urban designers often created polder cities as “a total scene” that made it easy for users to “identify its parts” and “structure the whole.” This statement suggests that spatial composition is likely a main contributor to the aesthetic coherence of water-centric cities. In this study, the author uses water urbanism to denote these potentially imageable water-centric cities that are characterized by a systematic integration of urban fabrics with waterscapes.

1.1.2. Relating the Definition of Imageability to Its Five Elements and Three Components

Lynch (1960) alluded to imageabilty as a pattern of high continuity with distinctive yet interconnected parts. This definition seems to suggest that imageability could be attributed to the combination of identity and structure provided by landmarks and uninterrupted paths and edges. Lynch (1960) did not, however, explicitly clarify or empirically test how this definition of imageability relates to his five elements of imageability (landmark, path, node, edge, and district) with reference to his three cognitive components of imageability (structure, identity, and meaning).

1.1.3. Comfort from Aquaphilia as Instinctual Human Affection Toward Water

Lynch (1960) pointed out that his participants' favorite views were usually panoramas with water and spatial openness. He also noted an emotional delight arising from his participants who mentioned broad views with water. Coss (1990) attributed people's preferences for water scenes and the optical properties of water, especially glossiness, to the evolutionary advantage of being able to identify clean drinking water. These observations suggest a possible association between water-based imageability and aquaphilia, which the author defines as an innate emotional bond with safe and clean water or water-centric environments. As comfort has been found to affect people's emotional connection with networks of open spaces and waterways (Mansor & Said, 2008), the extent to which water helps participants relax was used to measure their aquaphilia sensitivity baseline.

1.1.4. Water-based Spatial Anchors as the Sixth Element of Imageability

Lynch (1960) described the Charles River as an edge in Bostonians' cognitive maps. Milgram (1976) noted the appearance of the river Seine among the first elements on many sketch maps of Paris. It is unclear if the salience of the river Seine in the cognitive maps for Paris may be attributed to its cognitive form as an edge or to its simple presence as water. In an imageability study conducted by De Jonge (1962) with visitors and residents in three Dutch water cities, waterscapes seemed to emerge as the first features in sketch maps regardless of the waterscapes' cognitive forms as elements of imageability. He also observed greater detail in sketch maps drawn at closer proximity to water bodies. These results suggest the high likelihood that water-based elements may be higher-order spatial anchors—organizers of spatial information in cognitive maps according the anchor-point theory (Golledge, 1992; Osmond, 1963). Such water-based spatial anchors may be the sixth element of imageability that emerges before other non-water paths, nodes, districts, and edges during recall of a cognitive map, regardless of its imageability element. The salience of waterscapes in cognitive maps as spatial anchors can be expected to contribute to the imageability of water cities and facilitate the formation of more coherent cognitive maps and images among newcomers and visitors. The aesthetic coherence of water urbanism may facilitate environmental familiarity with cities, and therefore make them more appealing as tourist destinations and places of residence.

1.1.5 In Search of Imageability for the Pluralistic City Image

Sketch maps have been used as a data source for design research since the 1960s. These studies, however, have not produced generalizable design principles that would facilitate the formation of a collective city image for the increasingly diverse and transient populations of globalized cities. Lynch (1960) used frequency counts to compile multiple sketch maps into a combined spatial representation to inform city-specific design prescriptions without accounting for individual differences in spatial cognition. De Jonge's (1962) descriptive cross-city comparison of sketch maps did not produce evidence-based design theories. Appleyard (1976) empirically derived an evaluation rubric to quantitatively analyze sketch maps against socioeconomic data. Although his method accounted for individual differences through group comparisons of sketch map indicators, his design recommendations were not obviously generalizable beyond the studied city of Ciudad Guayana. His sketch map rubric was not based on spatial cognition theories, and the rubric was not tested for its validity and reliability. Instead, he used a data-driven approach to derive his rubric from observations of the major typologies in the sketch maps he collected from only the studied city.

1.2. Study Goal and Objectives

The main goal of this study was to investigate the feasibility of a multi-sited research design for examining how urban waterscapes contributed to the perceived coherence of a water-city image for visitors and residents of varying aquaphilia sensitivity baselines and socioeconomic characteristics, such as gender, age, education, and income. To achieve this goal, the author first proposed and tested the reliability of a rubric informed by spatial cognition theories in behavioral geography to quantify the coherence of sketch maps from multiple cities. For deriving potentially generalizable imageability theories beyond one city, the author then analyzed the relationships between the city-level imageability, as indicated by sketch-map coherence scores, and waterscape-specific imageability. Waterscape-specific imageability was operationalized by the five elements and three components of imageability as the variables of waterscape mappability, identifiability, and attachment. These three waterscape variables were measured by spatial memory recall frequency counts of waterscapes from cognitive mapping, photovoice, and emotional recollection protocols. By investigating the effects of these variables on sketch map coherence, this study strived to provide insights on the relative egocentric (eye-level), allocentric (top-down or map-like), and emotional salience of waterscapes as spatial anchors. This inquiry also aimed to clarify how to operationalize imageability as a compositional concept for environmental configuration using Lynch's five elements and three components in the context of water-centric cities. Furthermore, this inquiry was conducted for uncolored and colored (with water elements highlighted in blue) sketch maps in the presence or absence of water's contribution to sketch map coherence. These comparisons revealed whether a water-based spatial anchor was a separate element from the five conventional elements of imageability.

1.3. Definition of Terms

To operationalize the notion of coherence as a criterion for assessing sketch maps, the author proposed evaluation rubrics based on the following six spatial knowledge types: declarative, procedural, hierarchical, topological, configurational, and projective.

1.3.1. Declarative

Golledge and Stimson (1997) used declarative to refer to an ability to recognize salient objects or scenes and ascertain their meanings. This landmark knowledge is the first stage for the development of spatial knowledge in new environments (Siegel & White, 1975). The author postulates that the declarative component is similar to landmark as an element of imageability proposed by Lynch (1960).

1.3.2. Procedural

Consistent with Golledge and Stimson (1997), procedural knowledge alludes to the rules that link declarative components or landmarks to develop route knowledge as a sequence of eye-level views or egocentric images of landmarks together with movement directions (Gillner & Mallot, 1998). The author postulates that procedural knowledge has parallels to path as an element of imageability (Lynch, 1960) and declarative relations as path structure cognitively instigate the element of node for imageability (Lynch, 1960).

1.3.3. Hierarchical

Gollege and Stimson (1997) employed hierarchical ideas to depict the mechanism underlying the development of survey knowledge as the spatial concept of a sequence of proximities to spatial anchors of different importance levels. The investigator posits that hierarchical components can be wayside landmarks along a path or landmarks around a node to form an edge as an element of imageability (Lynch, 1960). In addition, hierarchical relations among spatial anchors of sequential orders spatially expand this linear spillover effect potentially to suggest systems of landmarks as declarative relations.

1.3.4. Topological

Golledge and Stimson (1997) used topological to describe spatial properties unaltered under elastic deformation by continuous planes, including proximity and separation, openness and enclosure, and dispersion and clustering. Piaget and Inhelder (1967) used topological to describe a transitional phase between egocentric and allocentric spatial knowledge. According to Lynch (1960), the district as an element of imageability is an aerial concept defined by the edge. Topological is thus construed here as a cognitively integrating ability to perceive urban districts based on the following assumptions: 1) The clustering of landmarks in proximity to a path potentially creates a sense of enclosure to form cognitive edges; 2) these edges help delineate open areas as districts in cognitive maps due to the edges' contrast with separated elements in dispersion; 3) edges can also be perceived due to the presence of linear spatial anchors, such as canals or rivers, or through sequencing wayside spatial anchors into a continuous boundary; and 4) a district can also be formed by clustering hierarchical knowledge in the form of a series of proximities spread from spatial anchors.

1.3.5. Configurational

Many have posited configurational abilities as a general term to describe the allocentric view of cognitive images with survey knowledge (Golledge & Stimson, 1997;

Kirasic, Allen, & Siegel, 1984). Similar to Merriam-Webster Dictionary's definition of configuration, Kaplan (1976) describes the cognitive map as a gestalt-like network of elements that act as a whole rather than as a mere assortment of elements. This study thus uses configurational to characterize the ultimate stage of allocentric or survey knowledge, where the wholeness of a figure or pattern becomes identifiable as more than a collection of declarative, procedural, hierarchical, and topological components and relations as elements of imageability.

1.3.6. Projective

This study adopts the Merriam-Webster Dictionary's definition for projective as "relating to, produced by, or involving geometric projection" because it is in line with Kuipers' (1978) and Montello's (1998) use of cognitive projective to describe abstract survey knowledge with inferred spatial components or relations.

1.4. Theory and Applications

1.4.1. The Effects of Gender and Visitors or Residents on Allocentric and Egocentric Coherence

Lawton (1994) discovered that women have a predisposition to use a more egocentric frame of reference to acquire landmark knowledge for sequencing into route knowledge, while men are more inclined to use an allocentric frame of reference to more quickly translate landmark knowledge into route and survey knowledge. College and Stimson (1997) pointed out newcomers may revert to a preoperational level of spatial comprehension dominated by typological knowledge typically acquired through egocentric cognition. It is unclear whether the dual-perspective sketch-map coherence differed between visitors and residents, or that visitors were more likely to use egocentric than allocentric perspective than residents. This study used allocentric and egocentric perspectives for probing recall spatial memory and evaluating sketch-map coherence. Its regression analyses also included a group variable for visitor versus resident, gender, income, education, and age to study possible group effects on sketch-map coherence.

1.4.2. Sketch-Map Coherence as a Measure of the Salience of Waterscapes as Spatial Anchors

Survey knowledge has often been assessed using sketch maps for studying spatial abilities (Beck & Wood, 1976; Evans, 1980). Blades (1990) validated test-retest reliability of sketch maps for evaluating spatial knowledge. This study asked participants to draw sketch maps only once. Sketch-map coherence has been found to correlate with environmental configuration (Kim & Penn, 2004) and to reflect environmental affordance for self-orientation (Southworth, Cranz, Lindsay, & Morhayim, 2012). De Jonge (1962) found that visitors and residents were likely to show a spatial arrangement composed of separate elements with clear identity in their sketch maps for locations where self-orientation was easy. Anchor-point theory (Golledge, 1992; Osmond, 1963) suggests that spatial anchors, including spaces of frequent interactions and commonly recognized places, tend to emerge first in cognitive maps as organizers of other spatial information due to spatial anchors' relatively higher level of significance to individuals. These observations suggest that spatial anchors as salient features for orientation and way-finding tend to emerge earlier during cognitive map and image recall procedures. These spatial anchors may be salient to the structure, identity, or meaning components of imageability proposed by Lynch (1960). The author assumed that the coherence of sketch maps might be influenced by the allocentric, egocentric, and emotional salience of cognitive map elements that correspond to the structure, identity, and meaning components of imageability, respectively. This study assessed these three cognitive map qualities using the cognitive image recall sequence based on the top-down, eye-level, and emotional perspectives to generate waterscape mappability, identifiablity, and attachment measures, respectively.

1.4.3. The Contribution of Egocentric Coherence to Water Landmark Identifiability and Allocentric Coherence

Using spatial syntax to analyze the environment and its representation as sketch maps, Kim and Penn (2004) discovered the contribution of locally integrated spatial configuration (egocentric coherence) to the recall frequency of configurational elements (landmarks or spatial anchors) and the global syntax of spatial configuration (allocentric coherence) in sketch maps. Applying this result to the underlying mechanism of water-based imageability as an aesthetic perception of water urbanism, the author postulated that linear waterscapes may help interconnect landmarks into a high-continuity pattern and increase egocentric coherence. Egocentric coherence, as the local integration of salient elements along waterfronts, may be associated with the recall salience of these water landmarks or spatial anchors and the allocentric coherence of sketch maps.

1.4.4. Education as a Control Variable for Informational Influences on Sketch-Map Coherence

Previous investigations into the influence of map exposure on sketch maps and spatial comprehension have been inconclusive. Some found no correlation between map exposure frequency and sketch-map accuracy (Devlin, 1976), while others noted spatial performance improvement due to map exposure (Devlin & Bernstein, 1995). Kreimer

(1973) discovered that the foregrounding of specific elements in environmental cognition were often associated with the extensive use of secondary information sources, such as television, newspapers, and radio. To study how direct environmental experience affected sketch map coherence, the author proposed education as a rough proxy for map exposure and secondary information sources.

1.4.5. Influences of Graphic Representational Capacities on Sketch-Map Coherence

Many sketch-map studies did not control for participants' graphic representational capacities (Anderson & Tindall, 1972; Rovine & Weisman, 1989). Yet Siegel (1981) found that map production skills confounded the process of extracting environmental knowledge from sketch maps. To control this potential confound, the author proposed scoring rubrics using the following categories of graphic representational abilities, as suggested by Moore and Golledge (1976): 1) Undifferentiated egocentric, 2) differentiated and partly coordinated, 3) abstractly coordinated and hierarchically integrated representational, and 4) hierarchically integrated representational levels. These categories off representational abilities roughly correspond to the following spatial knowledge types: 1) Declarative/procedural, 2) hierarchical/topological, 3) configurational/projective, and 4) metric. Egocentric, typological, projective, and metric knowledge types dominate the environmental cognition of the sensory-motor, preoperational, concrete operational, and formal operational development stages proposed by Piaget and Inhelder (1967). Egocentric knowledge is embedded within the declarative and procedural categories for the proposed rubrics. While Golledge and Stimson (1997) used configurational cognition as a generic term to refer to allocentric knowledge, Kuipers (1978) and Montello (1998) repurposed this term as a transitional phase between qualitative (typological) to quantitative (metric) spatial knowledge. As this study is not concerned with the quantitative accuracy of sketch maps, metric cognition was not investigated.

Assuming the presence of significantly different graphic representational capacities among participants, scoring scheme A used configurational to denote a distinctive stage between the topological and projective categories. Configurational refers to the most common allocentric knowledge as concrete relations of actual elements, rather than as an abstraction of inferred relationships that characterize projective. Topological refers to a transitional phase between egocentric and allocentric; that is, it is a kind of configurational knowledge (Golledge & Stimson, 1997; Piaget & Inhelder, 1967).

Scoring scheme B posited no significant difference for participants' graphic representational capacities and therefore no distinction among topological, configurational, and projective knowledge types. These knowledge types were then consolidated as allocentric knowledge, while egocentric knowledge alluded to declarative and procedural knowledge. These delimitations of allocentric and egocentric knowledge led to the positioning of hierarchical as an intermediate stage between egocentric and allocentric knowledge.

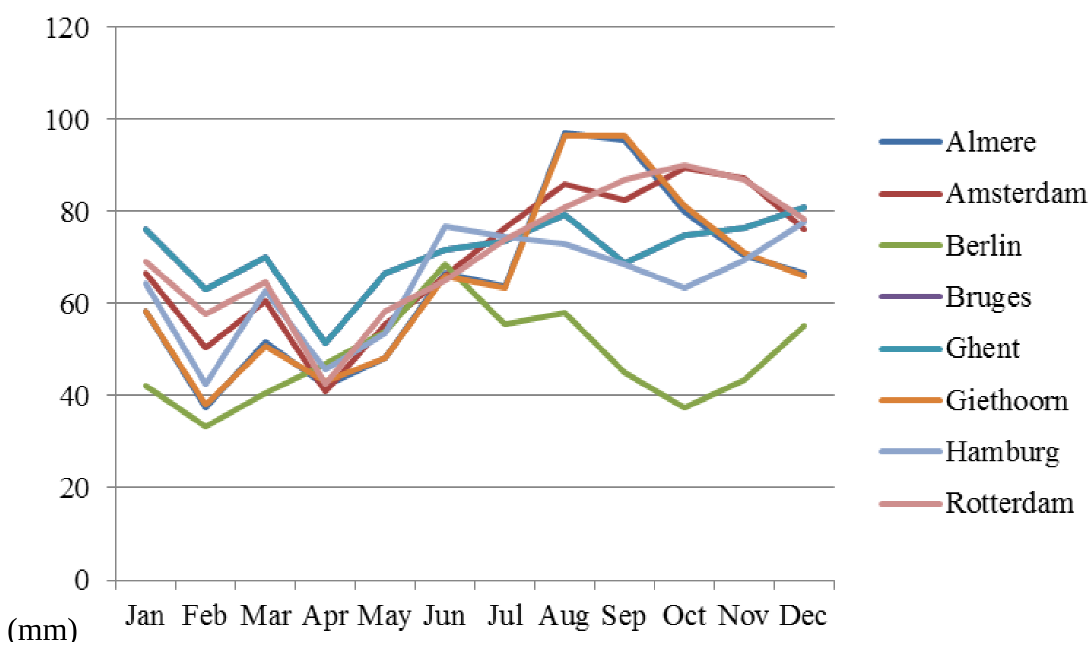
In contrast, scoring scheme C hypothesized that all spatial knowledge types beyond declarative and procedural components belonged to the overarching category of survey knowledge characterized by relations. Declarative relations refer to systems of landmarks as regional patterns of interrelationships between salient features, such as buildings, movements, or bridges. Procedural relations denoted path structures in the sense of interconnections of route knowledge for sequencing landmarks. Hierarchical components described ordered immediacies around landmarks or paths as spatial anchors versus a sequence of proximities around systems of landmarks or path structures for hierarchical relations.

2. Methods

2.1. Selection of Water Cities

Google search indicated that 12 cities have been referred to as “Venice of the North” because of their water-based appeal to visitors and residents. Wikipedia provides a list of 10 such cities: Amsterdam, Bruges, Copenhagen, Giethoorn, Hamburg, Henningsvær, Manchester, 's-Hertogenbosch, Saint Petersburg, and Stockholm. Berlin (MacLean, 2011) and Ghent (Raplee, 2010) have also been compared to Venice. Among this shortlist of alluring water cities, the author chose six as study sites based on precipitation pattern similarity (Figure 3.1.) and geographical proximity for cost of sampling as selection criteria.

Figure 3.1. Precipitation patterns in water cities



These first six cities selected were Amsterdam and Giethoorn in the Netherlands, Ghent and Bruges in Belgium, and Berlin and Hamburg in Germany. Only Amsterdam and Hamburg are coastal cities with harbors in proximity; the other four are inland water cities. Rotterdam and Almere, the two fastest-growing polder cities in the Netherlands, were also appealing water cities with easily accessible harbors (Kwadijk et al., 2010; Tao & Zhengnan, 2013). These two coastal polder cities were thus added to the selection of study sites, for a total of eight cities.

2.2. Recruitment of Field Participants

A simple and obvious sampling frame for residents and tourists in these eight cities does not exist. The author therefore randomly sequenced sampling sites to create an approximation of a random sample to represent a theoretical sampling frame. This theoretical sampling frame assumed it was possible to capture all residents and visitors in each water city. The investigator used a randomized order to sequence the eight cities. Each city’s nine sampling sites always included major entry points (such as airports, inter-city train stations, and bus stations), city halls, and tourist bureaus, and various hotels, cafés, ethnic stores, and universities. The author chose these sites to sample a representative mix of residents and visitors, high- and low-income populations, environmental design experts and non-experts, and immigrants and visitors from various countries of origin. Each sampling site was sampled for 5 hours, for a total of 45 hours for each water city.

2.3. Field Data Collection

The author recruited 60 semi-structured interview participants from sampling sites in all eight cities. As shown in Table 3.1., during each interview, the investigator conducted cognitive mapping (item 1), photovoice (item 3), and non-visual protocols (item 4) to prompt the participant to recall the city as the first five features to emerge from a two-dimensional top-down cognitive map, the first five photograph-like eye-level cognitive images to surface from spatial memory, and the five elements that would be most missed if the participant had to leave the city the next day. The author used these three recall protocols to assess the mappability, identifiability, and attachment of five waterscape types in relation to their allocentric, egocentric, and emotional salience in spatial memory.

Table 3.1. Interview items and coding for environmental factor variables

Variables	Interview items for field participants
Waterscape mappability[ab]	1. Cognitive mapping protocol: Imagine you are drawing a map of the city. Please name or describe the five features or locations that come to mind first. Please do not consult a city map.
Coherence[c]	2. Sketch map protocol: Please draw a map of your city on the next page. Include as many features as you can recall. Number the features directly on the map to indicate the sequence in which they emerged from your memory.
Waterscape identifiability[ab]	3. Photovoice protocol: If you were to take five pictures of the city to describe it to someone who has never been there, what would you take pictures of?
Waterscape attachment[ab]	4. Non-visual protocol: What are the five things you would miss about the physical environment if you had to leave the city tomorrow?

a. Code each answer 1 or 0 based on whether it contains a target waterscape, assign a weight from 5 to 1 to account for the sequence of recall, and use a weighted average to create variable measures.

b. A targeted waterscape can be a canal, river, lake, harbor, or a water landmark (a landmark along and/or across a body of water).

c. The sketch map was used to generate various coherence measures as described in Section 2.5.2.

The targeted waterscape types included canal, river, lake, harbor, and water landmark (a landmark along and/or across a body of water). Immediately after the cognitive mapping protocol, the investigator conducted the sketch-map protocol (item 2) to instruct each participant to draw a map of the city while keeping track of the sequence in which each feature appeared in his or her memory. Some 60 interviews resulted in 55 sketch maps because 5 participants could not draw their cognitive maps from recall. Table 3.2. illustrates other interview questions for measuring individual factors.

Table 3.2. Interview items and coding for individual factor variables

Independent variables	Interview items for field participants Coding
Age	5. In what year were you born? (convert answer to age)
Aquaphilia baseline[a]	6. If you could live anywhere, would you choose to live? □ Right on the water (5) □ With easy access to water (4)□ With visual access to water only (3) □ Far away from water (2) □ As far away from water as possible (1)
Education[a]	7. What is the highest level of education you have completed? □ Graduate degree (5) □ Higher education (Bachelor's degree) (4) □ Some college (3) □ Secondary school (2) □ Elementary school (1)
Gender	8. Which sex or gender do you identify with? □ Female (2) □ Male (1) □ Other (0)
Income[a]	9. Approximately what was your total household income for 2012? Please include all income sources for every member in your household. □ Less than €15,000 (4) □ €15,000–€30,000 (3) □ €30,000–€45,000 (2) □ More than €45,000 (1)
Visitor/ Resident	10. How many years/days have you lived in this city (altogether)? Code length of exposure with 1 or 2 for less than or more than 90 days, respectively, to differentiate visitors from residents.

a. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses.

2.4. Coding for Field Data

For items 1, 2, and 4 in Table 3.1., the investigator assigned a base score of 1 or 0 to each response depending on whether it contained one of the five targeted waterscapes. The basis for classifying these waterscapes was on the literal use of the waterscape terms or the names of actual water bodies in participants' responses. When a waterscape type was unclear in a response, the investigator asked the participant to clarify before ending the interview. The author applied a weight of 5 to the base score for the first answer, 4 for the second, and so forth, to account for the significance of each waterscape type's recall sequence. As shown in the following formula, the investigator took a weighted average from the sum of all five weighted base scores:

Weighted average = (5 * first answer base score + 4 * second answer base score
+ 3 * third answer base score + 2 * fourth answer base score
+ 1 * fifth answer base score) / 5

This formula was used to derive, from the results of the cognitive mapping, photovoice, and non-visual recall protocols in Table 3.1., the mappability, identifiability, and attachment measures, respectively, for canal, harbor, lake, river, and water landmark.

As shown in Table 3.2., the investigator used a five-point Likert scale to ordinate the score for aquaphilia baseline (item 6) and education (item 7), and a four-point scale for income (item 9). For gender (item 8), female and male were coded 2 and 1, respectively. Each participant's birth year was subtracted from 2015 to calculate age (item 5). Length of exposure was coded as 1 or 2 if it was less or more than 90 days, respectively, for the group variable of visitor versus resident because the Schengen visitor visa allows its holder to stay up to 90 days.

2.5. Sketch Map Evaluation Protocol

Several studies utilized two independent raters to score or analyze sketch maps to establish inter-rater reliability for measures that could be influenced by subjective judgments (Ferguson & Hegarty, 1994; Maguire, Burke, Phillips, & Staunton, 1996; Quaiser-Pohl, Lehmann, & Eid, 2004). Two independent raters without previous exposure to either the study or the eight cities were recruited for two evaluations of the 55 sketch maps using two rubrics and pre-survey briefing materials. These 55 maps were presented in a randomized sequence for each rubric in Qualtrics, which enabled raters to assign ratings to each sketch map. To control potential data entry errors and collect insights for improving rubric 1, the investigator instructed the two raters to keep track of their ratings in Qualtrics using a paper scoring sheet, and to provide one sentence describing their reasons for each rubric category.

2.5.1. Survey 1 with Raters 1 and 2 Using Rubric 1 with Uncolored Sketch Maps

Appendix A shows rubric 1 and the pre-survey briefing readings provided to raters 1 and 2 for the first sketch map survey. The pre-survey readings included Lynch's (1960, pp. 46-49) explanations for landmark, path, node, edge, and district excerpted from *The Image of the City*, a verbatim passage of the anchor-point theory from *Spatial Behavior* (Golledge & Stimson, 1997, p. 167), and the Merriam-Webster Dictionary definitions of topological and configurational.

During the first survey, raters 1 and 2 had difficulty discerning the extent to which a sketch map covers the entire city and the differences between projective versus concrete spatial components and relations. Based on the raters' written explanations for their rubric 1 ratings, both raters had difficulty discriminating components from relations within each of the rubric's six implicit spatial knowledge categories: declarative, procedural, hierarchical, topological, configurational, and projective.

2.5.2. Survey 2 with Raters 1 and 2 Using Rubric 2 with Uncolored Sketch Maps

To address these two observations from survey 1 results, the investigator added 8 city maps in the pre-survey briefing materials for the second survey and used the raters' verbal explanations from survey 1 to revise rubric 1 into rubric 2 in Table 3.3. Rubric 2 made explicit the 6 spatial knowledge types as components and relations. The author also added the definitions of these spatial knowledge types to the revised pre-survey briefing materials exhibited in Appendix B.

Table 3.3. Proposed rubric two for sketch map evaluation

Please select one statement that best describes the sketch map. This sketch map appears to:	
Declarative component	1. Show an impressionist sketch of landmark/node characteristics.
Declarative relations	2. Illustrate randomly distributed landmarks/nodes unconnected by paths.
Procedural component	3. Display landmarks/nodes as destinations connected by paths yet with little information about pure path intersections or wayside landmarks.
Procedural relations	4. Exhibit path segments without wayside landmarks but with some pure path intersections that seem to have been drawn from turn-by-turn instructions.
Hierarchical component	5. Reveal landmarks/nodes in proximity to major paths, landmarks, or nodes without enough pure path intersections to enable shortcut-taking.
Hierarchical relations	6. Reveal landmarks/nodes in proximity to major paths, landmarks, or nodes with enough pure path intersections to enable shortcut-taking.
Topological component	7. Contain districts that can be delineated based on continuous edges or clusters of landmarks/nodes.
Topological relations	8. Show a nested hierarchy of multiple districts that can be delineated based on continuous edges or clusters of landmarks/nodes.
Configurational component	9. Indicate a distinct form that resembles only a small part of the city center.
Configurational relations	10. Capture the entire city structure as one single configuration or a collective pattern greater than the sum of multiple distinct forms.
Projective component	11. Suggest abstract components from known topological or configurational components instead of district-defining edges on the ground.
Projective relations	12. Infer abstract relationships from known topological or configurational relationships instead of actual physical relationships between districts.

During the second survey, raters 1 and 2 were guided by written instructions to first select a rubric description for each sketch map and then glance at the 8 city maps for no longer than 10 seconds to determine whether they could recognize the city represented by each sketch map (item 1 in Table 3.4.). The author assigned a code of 1 or 0 to this item when each sketch map was identified successfully or not, respectively, to generate the measure of uncolored allocentric coherence (UAC) based on the identifiability of uncolored sketch maps.

2.5.3. Survey 3 with Raters 3 and 4 Using Rubric 2 with Colored Sketch Maps

For the third sketch-map survey, the investigator colored the water elements in the 55 sketch maps in blue before presenting them at random to raters 3 and 4, who had no previous exposure to the study or briefing materials. For each sketch map, the investigator provided written instructions, asking the raters to choose the best-fitting rubric category and then scan 8 city maps for no longer than 10 seconds to identify the city associated with each colored sketch map (item two in Table 3.4.). The author then assigned a code of 1 for correct and 0 for incorrect and unsure identification of each sketch map to generate the measure for the variable of colored allocentric coherence (CAC) based on the identifiability of colored sketch maps.

For water-based coherence measures, survey 3 asked raters 3 and 4 to evaluate the extent to which non-blue features cluster along blue features (item 3 in Table 2.4.) and the contribution of blue features to the identifiability of each map (item 4 in Table 2.4.). Both items assumed their 3 response categories as equally spaced points along a 3-point Likert scale to generate scores for water-based egocentric coherence (WEC) and contribution of water (CW), respectively. The measure for water-based allocentric coherence (WAC) was generated by multiplying colored allocentric coherence (CAC) times the contribution of water (CW).

Table 3.4. Survey questions and coding schemes for non-rubric-based coherence measures

Variable	Descriptive Name	Colored sketch map survey items Coding schemes
UAC[ac]/ CAC[bc]	Uncolored/Colored allocentric coherence	1. This is a map of what city? □ Almere □ Amsterdam □ Berlin □ Bruges □ Ghent □ Giethoorn □ Hamburg □ Rotterdam □ Not Sure
WEC[d]	Water-based egocentric coherence	3. To what extent do non-blue features cluster along blue features? □ Very much (3) □ Somewhat (2) □ Not (1)
CW[d]	Contribution of water	4. To what extent do the map's blue features help you identify the city? □ Very much (3) □ Somewhat (2) □ Not (1)
WAC	Water-based allocentric coherence	5. The contribution of water to correct colored map identification. Colored allocentric coherence (CAC) * contribution of water (CW)

a. For raters 1 and 2 during the second sketch map survey using uncolored sketch maps.
b. For raters 3 and 4 during the third sketch map survey using colored sketch maps.
c. Code 1 for correct or 0 or incorrect/unsure responses.
d. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses.

2.5.4. Sketch Map Coding Schemes Based on Numbers of Spatial Knowledge Stages

The investigator also generated 7 rubric-based coherence measures (3 dual-perspective coherence and 4 allocentric coherence measures) in Table 3.5. by coding the ratings from the second survey with the 7 scoring schemes in Table 3.6. Twelve-stage coherence (12C) was produced from coding rubric 2 ratings with scheme A, which hypothesized that all knowledge types were distinct stages of spatial cognition that developed as represented by a Likert scale of 12 equally spaced points. Using an 8-point Likert scale, scheme B posited that topological, configurational, and projective were interchangeable terms for describing the most advanced qualitative state of a sketch map, while declarative, procedural, and hierarchical were distinct categories along a gradient for the development of spatial knowledge. Coding rubric 2 ratings with scheme B created scores for 8-stage coherence (8C). Finally, with a 3-point Likert scale, scheme C postulated that differences were found only among 3 gradually more elaborated states of spatial comprehension as declarative, procedural, and survey knowledge, which referred to all spatial knowledge types beyond declarative and procedural categories. The investigator used scheme C to code rubric 2 ratings to derive values for 3-stage coherence (3C).

Table 3.5. Coding schemes for rubric-based coherence measures

Dual-perspective coherence	Scheme	Allocentric coherence	Scheme
Twelve-stage coherence (12C)	A	Projective coherence (PC)	D
Eight-stage coherence (8C)	B	Configurational coherence (CC)	E
Three-stage coherence (3C)	C	Topological coherence (TC)	F
		Hierarchical coherence (HC)	G

Table 3.6. Proposed sketch map evaluation rubric coding schemes knowledge type

	A	B	C	D	E	F	G
1.Declarative component	1	1	1	0	0	0	0
2.Declarative relations	2	2	3	0	0	0	0
3.Procedural component	3	3	2	0	0	0	0
4.Procedural relations	4	4	3	0	0	0	0
5.Hierarchical component	5	5	3	0	0	0	1
6.Hierarchical relations	6	6	3	0	0	0	1
7.Topological component	7	7	3	0	0	1	1
8.Topological relations	8	8	3	0	0	1	1
9.Configurational component	9	7	3	0	1	1	1
10.Configurational relations	10	8	3	0	1	1	1
11.Projective component	11	7	3	1	1	1	1
12.Projective relations	12	8	3	1	1	1	1

2.5.5. Coding Schemes for Allocentric Coherence Based on Sketch Map Identifiability

The 4 measures of allocentric coherence in Table 3.6. were generated based on 4 premises concerning the minimal spatial knowledge types required for making a sketch map identifiable. The investigator tested these 4 hypotheses by triangulating the 4 allocentric coherence indicators with the 2 map identifiability measures: uncolored and colored allocentric coherence in Table 3.4. Among the 4 coding schemes for allocentric coherence measures in Table 3.5., scheme D for projective coherence (PC) assumed that only projective knowledge contributed to allocentric coherence by assigning a dummy code of 1 to projective components and relations, and 0 to other spatial knowledge types. Scheme E for configurational coherence (CC) hypothesized that allocentric coherence required at least configurational knowledge by dummy-coding configurational and projective components and relations as 1 and other categories as 0. Scheme F for topological coherence (TC) assigned 1 as a dummy code to topological, configurational, and projective components and relations and 0 to other classifications based on the assumption that allocentric coherence necessitated no less than topological knowledge. Finally, scheme G for hierarchical coherence (HC) postulated that allocentric coherence was attributed to hierarchical knowledge as a bare minimum via allocating 1 to hierarchical, topological, configurational, and projective components and relations and 0 to other states of spatial cognition.

2.6. Data Analysis

The investigator calculated the intra-class correlation coefficients (ICCs) of all coherence measures in Table 3.6. in SPSS 22 using a 2-way mixed model and an absolute agreement definition, as suggested by McGraw and Wong (1996), to assess their reliabilities between raters and measures. Along with the Cronbach's alpha as a commonly used inter-rater and internal consistency reliability indicator, SPSS provided the ICC average measure to assess the proportion of a variance attributable to judges for the average ratings of two independent raters.

ICC values between 0.60 and 0.74 are commonly cited as cutoffs for good inter-rater reliability (Cicchetti, 1994; Hallgren, 2012). Several studies used 0.6 as an acceptable ICC threshold (Baumgartner & Chung, 2001; Ostroff & Schmitt, 1993) and as an acceptable threshold for determining internal consistency reliability with Cronbach's alpha (Hume, Ball, & Salmon, 2006). As the lower bound of a reliability coefficient, Cronbach's alpha does not require measures of precision, such as confidence intervals (Cronbach, 1951). This study used 0.6 as the cut-off value for both ICC and Cronbach's alpha to qualify reliability between raters and measures.

Each reliability coherence measure was then employed as a dependent variable with all 15 independent waterscape variables in Table 3.1. in a subtractive stepwise regression analysis, which eliminated variables whose omissions did not result in a significant F-value change. The investigator subsequently conducted an additive stepwise regression analysis with the 6 factors in Table 3.2. These 6 factors were added to the stepwise regression as independent variables one at a time with the significant waterscape variables identified by the subtractive stepwise regression analysis. If a change in F-value was significant due to the addition of an independent variable, the variable was retained in the final regression model for each coherence measure as the dependent variable. A power analysis conducted in G*Power 3.1.9.2 (Appendix C) suggested that the sample size ($N=55$) provided sufficient power ($d=0.804>.8$, $\alpha=0.05$) for regression models with one dependent variable and five independent variables. The regression model R^2 was evaluated based on Cohen's (1988) standards of 0.02 for small, 0.13 for medium, and 0.26 for large effect sizes.

3. Results

Appendices 3D and 3E shows the results of all inter-rater reliability and internal consistency reliability tests, respectively, conducted in SPSS using Cronbach's alpha and ICC average measure. Appendix F exhibits the original SPSS outputs for the regression analysis results discussed below.

3.1. Inter-rater Reliability

With 0.6 as an acceptable threshold for Cronbach's alpha and ICC average measure (McGraw & Wong, 1996), the 12-stage coherence (12C) and eight-stage coherence (8C) from rubric 1 ratings did not have sufficient inter-rater reliability (α_{12C} =.3<.6, ICC_{12C} =.3<.6, p_{12C}>.05; α_{8C} =.2<.6, ICC_{8C} =.3<.6, p_{8C}>.05). Although the 3-stage coherence (3C) for rubric 1 was reliable (α_{3C} =.7>.6, ICC_{3C} =.7>.6, p_{3C}<.001), it was excluded due to the aforementioned flaws of rubric 1. The first 2 raters' written descriptions indicated that rubric 2 and the revised briefing materials enabled adequate differentiation of the 6 spatial knowledge categories and their respective components and relations. Table 3.7. summarizes the results of inter-rater reliability test for the second and third sketch map surveys. The author chose 12-stage coherence (12C), 8-stage coherence (8C), projective coherence (PC), and topological coherence (TC), the average ratings from the rubric 2, as coded with schemes A, B, D, and F, as possible coherence measures because their Cronbach's Alpha and ICC average measures were significantly greater or equal to 0.6 (α_{12C} =.7>.6, ICC_{12C}=.6, p_{12C}<.001; α_{8C} =.6, ICC_{8C} =.6, p_{8C}<.001; α_{PC} =.6, ICC_{PC} =.6,

p_{PC}<.001; α_{TC} =.7>.6, ICC_{TC} =.6, p_{TC}<.001). Both map identifiability measures, uncolored allocentric coherence (UAC) and colored allocentric coherence (CAC), were reliable (α_{UAC} =.7>.6, ICC_{UAC}=.7>.6, p_{UAC}<.001; α_{CAC} =.7>.6,ICC_{CAC} =.7>.6, p_{CAC}<.001). Acceptable inter-reliability was also observed for water-based allocentric coherence (WAC) and water-based egocentric coherence (WEC) (α_{WAC} =.7>.6, ICC_{WAC}=.7>.6, p_{WAC}<.001; α_{WEC} =.7>.6, ICC_{WEC} =.6, p_{WEC}<.001).

Table 3.7. Inter-rater reliability of sketch map coherence measures

	12C	8C	3C	PC	CC	TC	HC	UAC	CAC	WAC	WEC
α^b	$.7^{***}$	$.6^{***}$	$.4^{*}$	$.6^{**}$	$.6^{**}$	$.7^{***}$	.4	$.7^{***}$	$.7^{***}$	$.7^{***}$	$.7^{***}$
ICC^c	$.6^{***}$	$.6^{***}$	$.4^{*}$	$.6^{**}$	$.5^{**}$	$.7^{***}$	.4	$.7^{***}$	$.7^{***}$	$.7^{***}$	$.6^{***}$

a. $^{*}p$<.05; $^{**}p$<.01; $^{***}p$<.001.
b. Cronbach's Alpha
c. Intraclass Correlation Coefficient based on two-way mixed effects, absolute agreement definition, and the assumption of zero interaction effect.

3.2. Internal Consistency Reliability

Table 3.8. summarizes the results of internal consistency reliability test using 0.6 as an acceptable threshold for Cronbach's Alpha and ICC Average Measure (McGraw & Wong, 1996).

Table 3.8. Internal Consistency Reliability of Sketch Map Coherence Measures

Measure 1	UAC	UAC	UAC	UAC	UAC	UAC	UAC	UAC	UAC
Measure 2	CAC	CAC	CAC	WAC	WAC	WAC	WEC	WEC	WEC
Measure 3		PC	TC		PC	TC		PC	TC
α^b	$.8^{***}$	$.7^{***}$	$.7^{***}$	$.7^{***}$	$.5^{***}$	$.6^{***}$	$.6^{**}$	$.5^{**}$	$.7^{***}$
ICC^c	$.8^{**}$	$.6^{***}$	$.7^{***}$	$.5^{***}$	$.4^{***}$	$.5^{***}$	$.2^{**}$	$.2^{**}$	$.3^{***}$

a. $^{**}p$<.01; $^{***}p$<.001.
b. Cronbach's alpha.
c. Based on two-way mixed effects, absolute agreement definition, and the assumption of zero interaction effect.

The 2-measure internal consistency reliability test showed that uncolored allocentric coherence (UAC) and colored allocentric coherence (CAC) were not significantly different ($\alpha_{UAC/CAC}$ =.8>.6, ICC $_{UAC/CAC}$=.8>.6 $_{UAC/CAC}$<.001).The author triangulated these two measures with projective coherence (PC) and topological coherence (TC), respectively, in 3-measure internal consistency reliability tests. Projective coherence (PC), that is, the identification of projective components and relations alone, exhibited an acceptable level of internal consistency reliability with the 2 map-identifiability-based allocentric coherence measures ($\alpha_{UAC/CAC/PC}$=.7>.6, $ICC_{UAC/CAC/PC}$=.6, $p_{UAC/CAC/PC}$<.001). This finding suggests that projective knowledge is a dominant allocentric cognition type associated with the identifiability of sketch maps. Topological coherence (TC), which combined projective, configurational, and topological components and relations into one composite category using scoring scheme F, had a slightly greater internal consistency reliability with uncolored allocentric coherence (UAC) and colored allocentric coherence (CAC) based on the ICC average measure ($\alpha_{UAC/CAC/TC}$ =.7>.6, $ICC_{UAC/CAC/TC}$=.7>.6, $p_{UAC/CAC/TC}$<.001). The result indicates that the graphic representational capacities of this participant sample did not significantly confound detection of these various coherence schemas. These 3 knowledge types are thus interchangeable instead of distinct spatial concepts for this participant sample. The allocentric knowledge for associating sketch maps with cities is distinct from hierarchical spatial relations. Hierarchical spatial knowledge is therefore likely to be a phase between egocentric and allocentric spatial cognition abilities.

3.3. Regression Analyses

3.3.1. Rubric Coherence Scores as Dependent Variables

As illustrated in Tables 3.9. and 3.10., 35% of the variance in 12-stage coherence (12C) and 43% in 8-stage coherence (8C) (R_{12C}^2=.35, F_{12C}(5, 49)=5.17, p_{12C}<.001; R_{8C}^2=.43, F_{8C}(5, 49)=7.36, p_{8C}<.001) could be explained by increases in water landmark identifiability (β_{12C}=.34, t_{12C} (49)=2.78,p_{12C}<.01; β_{8C}=.37, t_{8C}(49)=3.23,p_{8C}<.01), river mappability (β_{12C}=.32, t_{12C} (49)=2.64, p_{12C}<.05; β_{8C}=.28, t_{8C} (49)=2.42,p_{8C}<.05), and canal mappability (β_{12C}=.26, t_{12C}(49)=2.10, p_{12C}<.05; β_{8C}=.26, t_{8C} (49)=2.25,p_{8C}<.05), and a decrease in aquaphilia baseline (β_{12C}=-.23, t_{12C}(49)=-1.96, p_{12C}<.10; β_{8C}=-.33, t_{8C} (49)=-3.05,p_{8C}<.01). Both final models were robust to multicollinearity because the tolerances of all 4 independent variables were above 0.8. Appendix F shows that these 2 models were free of heteroscedasticity and outliers because the relationship between the standardized predicted value and standardized residual was fairly random in both regression scatter plots.

The dual-perspective coherence of water urbanism, as expressed in participants' sketch maps, was associated with water landmark identifiability and the mappability of rivers and canals. Water landmark identifiability may be associated with the egocentric salience of water landmarks, while the mappability of rivers and canals may be related to the allocentric prominence of water-based paths, rivers, and canals in participants' cognitive maps. The finding supports the feasibility of rubric 2 and spatial memory recall protocols for assessing waterscape effects on the allocentric and egocentric coherence of a cognitive image of cities.

Table 3.9. Regression model summary and ANOVA for predicting dual-perspective coherence

Dependent Variable (*x*)	R	$R_x{}^2$	$R_x{}^2$_a	SE	df_m	df_r	F
12-stage coherence *(12C)*	.59[b]	.35	.28	2.74	5	9	5.17^{***}
8-stage coherence *(8C)*	.66[b]	.43	.37	1.69	5	9	7.36^{***}

a. $^{***}p<.001$.

b. Predictors: (Constant) Visitors or residents, aquaphilia baseline, canal mappability, river mappability, water landmark identifiability

Although the first independent variable, the group variable of visitors or residents, was significant in the additive stepwise regression models (β_{2A}=.30, $t_{2A}(53)$=2.28, p_{2A}<05; β_{2B}=.35, t_{2B} (53)=2.70,p_{2B} <0.1), it became insignificant in the final regression models for both dependent variables, 12-stage and 8-stage coherence (β_{2A}=.13, $t_{2A}(49)$=1.03, p_{2A} =.31>.05; β_{2B}=.16, t_{2B} (49)=1.42,p_{2B} =.16>.05). Water landmark identifiability, river mappability, and/or canal mappability may potentially mediate the significant group effect of visitors or residents on both dual-perspective coherence scores. The regression model was enhanced by combining topological, configurational, and projective categories into one category for the 8-stage coherence (8C) measure, as opposed to keeping them distinct for the 12-stage coherence (12C) measure: more variation in the dependent variable was explained by the 8-stage coherence model because the regression R-square increased from 0.35 to 0.43. The influence of aquaphilia sensitivity baseline on the coherence score increased, as its standardized coefficient amplified from -0.23 to -0.33.The results indicate that the influence of graphic representational abilities may be ignored for this sample. In addition, the consolidation of these three categories increased the influence of water landmark identifiability on the coherence score (β_{12C}=.34, β_{8C}=.37) and decreased the effect of river mappability (β_{12C}=.32, β_{8C}=.28) without affecting the effect of canal mappability (β_{12C}=.26, β_{8C}=.26). The finding potentially suggests that water landmark identifiability, canal mappability, and river mappability may be associated with topological, configurational, and projective spatial knowledge, respectively.

Table 3.10. Regression coefficients for dual-perspective coherence measures

	Unstandardized coefficients					Collinearity statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Dependent Variable: 12-stage coherence*(12C)*							
(Constant)	5.52	1.68		3.29	.002		
Visitors or residents	.81	.78	.13	1.03	.31	.89	1.12
Aquaphilia baseline	-1.03	.53	-.23	-1.96	.056	.98	1.02
Canal mappability	.31	.15	.26	2.10	.041	.89	1.12
River mappability	.48	.18	.32	2.64	.011	.90	1.11
Water landmark identifiability	.37	.13	.34	2.78	.008	.89	1.12
Dependent Variable: 8-stage coherence *(8C)*							
(Constant)	5.10	1.03		4.94	.000		
Visitors or residents	.69	.48	.16	1.42	.16	.89	1.12
Aquaphilia baseline	-.99	.33	-.33	-3.05	.004	.98	1.02
Canal mappability	.20	.09	.26	2.25	.029	.89	1.12
River mappability	.27	.11	.28	2.42	.019	.90	1.11
Water landmark identifiability	.27	.08	.37	3.23	.002	.89	1.12

3.3.2. Allocentric Coherence Measures as Dependent Variables

Tables 3.11. and 3.12. illustrate the final regression results for three map-identifiability-based allocentric coherence measures with independent variables that significantly improved their subtractive and additive stepwise regression results.

Education was a significant independent variable for colored allocentric coherence (CAC) and marginally significant for water-based allocentric coherence (WAC).

Table 3.11. Model summary and ANOVA for predicting allocentric coherence

Dependent variable (*x*)	R	R_x^2	R_x^2_a	SE	df_m	df_r	F
Uncolored allocentric coherence *(UAC)*	.57[b]	.32	.28	.37	3	51	7.96***
Colored allocentric coherence *(CAC)*	.62[b]	.38	.35	.35	3	51	10.53***
Water-based allocentric coherence *(WAC)*	.70[b]	.48	.45	.81	3	51	15.78***

a. ****p*<.001.

b. Predictors: (Constant) Aquaphilia baseline, canal mappability, education

For comparison, education was included for the uncolored allocentric coherence (UAC) model, although it did not significantly improve its additive stepwise regression ($\Delta F_{UAC}(1,53)=.91$, $p_{UAC}=.35>.05$). Some 32% of the variance in the uncolored allocentric coherence (UAC) ($R_{UAC}^2=.32$, $F_{UAC}(3, 51)=7.96$, $p_{UAC}<.001$) could be attributed to the significant positive effect of canal mappability ($\beta_{UAC}=.47$, t_{UAC} $(51)=4.02$,$p_{UAC}<.001$) and the significant negative effect of aquaphilia baseline ($\beta_{UAC}=-.30$, t_{UAC} $(51)=-2.61$, $p_{UAC}<.05$) with education, or map and informational exposure, as an insignificant control variable ($\beta_{UAC}=.10$, t_{UAC} $(51)=.83$, $p_{UAC}=.41>.05$).

In contrast, for colored sketch maps, 38% of the variance in their allocentric coherence (CAC) ($R_{CAC}^2=.38$, $F_{CAC}(3, 51)=10.53$, $p_{CAC}<.001$) and 48% in their water-based allocentric coherence (WAC) ($R_{WAC}^2=.48$, $F_{CAC}(3, 51)=15.78$, $p_{CAC}<.001$) could be explained by the significant positive influences of canal mappability ($\beta_{CAC}=.47$, $t_{CAC}(51)=4.23$,$p_{CAC}<.001$; $\beta_{WAC}=.56$, $t_{WAC}(51)=5.51$,$p_{WAC}<.001$), the significant and marginally significant positive influences of education, or map and informational exposure ($\beta_{CAC}=.24$, $t_{CAC}(51)=2.11$, $p_{CAC}<.05$; $\beta_{WAC}=.19$, $t_{WAC}(51)=1.82$,$p_{WAC}=.07<.10$), and the significant negative influences of aquaphilia baseline (β_{CAC}=-.32, $t_{CAC}(51)$=-2.87, p_{CAC}<.01; β_{WAC}=-.36, $t_{WAC}(51)$=-3.57, p_{WAC}<.001).

Table 3.12. Regression coefficients for predicting allocentric coherence measures

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Dependent Variable: Uncolored Allocentric Coherence (*UAC*)							
(Constant)	.50	.25		1.99	.052		
Canal Mappability	.08	.02	.47	4.02	.000	.98	1.02
Aquaphilia Baseline	-.18	.07	-.30	-2.61	.012	.99	1.01
Education	.04	.05	.10	.83	.413	.98	1.03
Dependent Variable: Colored Allocentric Coherence *(CAC)*							
(Constant)	.28	.24		1.18	.244		
Canal Mappability	.08	.02	.47	4.23	.000	.98	1.02
Aquaphilia Baseline	-.19	.07	-.32	-2.87	.006	.99	1.01
Education	.11	.05	.24	2.11	.039	.98	1.03
Dependent Variable: Water-Based Allocentric Coherence *(WAC)*							
(Constant)	.95	.54		1.74	.088		
Canal Mappability	.22	.04	.56	5.51	.000	.98	1.02
Aquaphilia Baseline	-.55	.15	-.36	-3.57	.001	.99	1.01
Education	.21	.12	.19	1.82	.074	.98	1.03

When the model accounted for the extent to which water contributes to colored map identifiability, the author observed several model improvements: 1) The positive influence of canal mappability and the negative influence of aquaphilia baseline increased, 2) The positive influence and significance of education or map and informational exposure as potential confounds decreased, and 3) As the tolerances of all variables were above 0.8, these 3 models were robust to multicollinearity.

Since education, or map and informational exposure, was insignificant for the allocentric coherence of uncolored maps, the salience of blue, which the investigator used to highlight water elements on a city map, may have contributed to its effect for colored maps. While education, or map and informational exposure, was significant for the allocentric coherence of colored maps, it was marginally significant for water-based allocentric coherence. That is, the allocentric coherence of colored maps was likely weighted by the contribution of water. It is possible that the contribution of water may have introduced other significant influences beyond the three significant predictors, namely, canal mappability, aquaphilia baseline, and education. Finally, Appendix F shows a negative linear trend between the standardized predicted value and standardized residual in the scatter plots for all three models. The trend suggests that all three models may be enhanced with additional significant variables to account for the remaining systematic pattern in the scatter plots.

3.3.3. Water-Based Allocentric and Egocentric Measures as Dependent Variables

Tables 3.13. and 3.14. illustrate the results of final regression models using all variables that significantly improved either the subtractive or additive stepwise regression models using the dependent variables of water-based allocentric and egocentric coherence, respectively. Some 48% of the variance in water-based allocentric coherence (WAC)(R^2_{WAC} =.48, $F_{WAC}(4, 50)=11.72$, $p_{WAC}<.001$) could be attributed to the significant positive effect of canal mappability (β_{WAC} =.55, $t_{WAC}(51)=5.22$,$p_{WAC}<.001$), the marginally significant positive effect of education, map and informational exposure (β_{WAC} =.18, $t_{WAC}(51)=1.77$,$p_{WAC}<.10$), and/or the significant negative effect of aquaphilia baseline (β_{WAC}=-.35, $t_{WAC}(51)=-3.27$, $p_{WAC}<.01$). While gender significantly improved the additive stepwise regression model (ΔF_{WAC} $(1,53)=4.35$, $p_{WAC}<.05$), it became insignificant in the final model (β_{WAC}=-.05, $t_{WAC}(51)=-48$, $p_{WAC}=64>.5$). The individual or combined effects of canal mappability, education, or aquaphilia baseline might have mediated the gender effect on water-based allocentric coherence.

Table 3.13. Final regression model summary and ANOVA for predicting water-based coherence measures

Dependent Variable (x)	R	$R_x{}^2$	$R_x{}^2$_a	SE	df_m	df_r	F
Water-Based Allocentric Coherence	.70[a]	.48	.45	.81	3	51	15.78***
Water-Based Egocentric Coherence	.72[b]	.51	.44	.55	7	47	7.07***

a. Predictors: (Constant), Aquaphilia Baseline, Canal Mappability, Education
b. Predictors: (Constant), Visitors or residents, Aquaphilia Baseline, Age, Income, Lake Attachment, Canal Mappability

Table 3.14. Regression coefficients[a] for predicting water-based coherence measures

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	T	Sig.	Tolerance	VIF
Dependent Variable: Water-Based Allocentric Coherence (*WAC)*							
(Constant)	1.09	.62		1.75	.087		
Canal Mappability	.22	.04	.55	5.22	.000	.93	1.07
Aquaphilia Baseline	-.53	.16	-.35	-3.27	.002	.92	1.09
Education	.21	.12	.18	1.77	.084	.97	1.03
Gender	-.12	.25	-.05	-.48	.635	.88	1.14
Dependent Variable: Water-Based Egocentric Coherence (*WEC)*							
(Constant)	2.38	.41		5.83	.000		
Canal Mappability	.13	.03	.49	4.39	.000	.84	1.19
Lake Attachment	.13	.05	.28	2.73	.009	.97	1.04
Aquaphilia Baseline	-.36	.11	-.35	-3.20	.002	.88	1.14
Age	-.001	.000	-.23	-2.08	.043	.87	1.15
Income	.17	.07	.28	2.59	.013	.93	1.08
Visitors or residents	-.29	.16	-.20	-1.86	.069	.89	1.12
Gender	-.07	.17	-.04	-.39	.702	.84	1.19

In contrast, 51% of the variance in the water-based egocentric coherence (WEC), or the extent of clustering non-water elements around water elements in colored sketch maps ($R_{WEC}{}^2$=.51, $F_{WEC}(7, 47)$=7.07, p_{WEC}<.001), could be explained by: significant positive influences of canal mappability (β_{WEC}=.49, $t_{WEC}(47)$=4.39,p_{WEC}<.001), lake attachment (β_{WEC}=.28, $t_{WEC}(47)$=2.73, p_{WEC}<.001), and income (β_{WEC}=.28, $t_{WEC}(47)$=2.61, p_{WEC}<.05); the significant negative influences of aquaphilia baseline (β_{WEC}=-.35, $t_{WEC}(47)$=-3.20, p_{WEC}<.001) and age (β_{WEC}=-.23, $t_{WEC}(47)$=-2.08, p_{WEC}<.05); and the marginally significant negative influence of being a resident rather than a visitor (β_{WEC}=-.20, t_{WEC} (47)=-1.86, p_{WEC}<.10).

Although gender marginally significantly improved the additive stepwise regression model (ΔF_{WEC} (1,53)=3.20, p_{WEC}=*.08*<.10), it became insignificant in the final model (β_{WEC}=-.04, $t_{WEC}(47)$=-39, p_{WEC}=*70*>.5). One or more of the independent variables mediated the gender effect on water-based egocentric coherence. These variables were mappability, lake attachment, income, aquaphilia baseline, age, and the group effect of visitors or residents. As the tolerances of all variables were above 0.8, both models were robust to multicollinearity. Both scatter plots in Appendix F, however, show a negative linear trend between the standardized predicted value and residual, indicating a non-normal distribution error.

4. Discussions and Conclusions

4.1. Spatial Knowledge for Map-Identifiability Allocentric Coherence

The triangulation of internal consistency reliability and regression results indicate that 8-stage coherence and topological coherence (based on coding schemes B and F) perform better than 12-stage coherence and projective coherence (generated from coding schemes 2A and 2D) in explaining the spatial knowledge types involved in making maps identifiable. Since scoring schemes B and F were based on a composite category of topological, configurational, and projective knowledge, these three knowledge types were likely to be substitutable as developmentally nuanced categories for controlling varying graphic representational capabilities. In addition, the findings also suggest hierarchical knowledge as an intermediate phase between egocentric coherence (based on declarative and procedural knowledge) and allocentric coherence (attributed to topological, configurational, and projective knowledge).

4.2. Canal Mappability as a Potential Mediator for the Effects of Gender and Familiarity

Canal mappability was the only significant effect of water urbanism for all three allocentric coherence measures based on map identifiability, including uncolored, colored, and water-based allocentric coherence. The comparison of regression models for 12-stage coherence and 8-stage coherence indicates that canal mappability was potentially associated with configurational knowledge, which rubric 2 defines as closely related to the concept of imageability: configurational relations are identifiable city structures derived from the interconnections of distinct forms as configurational components. Future research may examine whether canal mappability alone could potentially moderate the significant gender effect on water-based allocentric and egocentric coherence and the significant group effect of visitors or residents on the two reliable dual-perspective coherence measures, namely, 12-stage coherence and 8-stage coherence. As aquaphilia baseline was a significant independent variable for all regression models, it should be included as a potential covariate in future mediation studies.

4.3. Water as a Separate Element of Imageability

For the coherence measures based on the identifiability of colored sketch maps, education was significant for allocentric coherence and marginally significant for water-based allocentric coherence. Participants with more education were more likely to produce identifiable colored sketch maps. This significant relationship became marginal, however, when accounting for water's contribution to the identifiability of these colored sketch maps. The findings suggest that although those with more education are more likely to have a higher level of map and informational exposure, participants' greater recall salience for blue water elements on cartographic maps and other informational sources may have been attributed to aquaphilia baseline rather than education. Furthermore, the significant effect of education on sketch map coherence was hidden for the allocentric coherence measure based on the identifiability of uncolored sketch maps. The result may indicate water as distinctively different from, and more cognitively powerful than, the conventional elements of imageability, which are paths, landmarks, nodes, edges, and districts.

4.4. Canal Mappability as the Nexus for Dual-Perspective Coherence

Dual-perspective coherence measures, 12-stage coherence and 8-stage coherence, were significantly associated in people's recall memory with the egocentric salience of water landmarks and the allocentric prominence of water-based paths, including rivers and canals. The result confirmed the dual-perspective of cognitive image. In addition, canal mapablity was found to be a significant independent variable for water-based allocentric and egocentric coherence (WAC and WEC). Overall, the findings suggest that canal mappability not only significantly contributes to the identifiability of sketch maps by providing configurational knowledge that makes a city imageable, but also serves as the nexus that connects the allocentric and egocentric perspectives into a unified dual-perspective cognitive image for water cities.

4.5. Water Urbanism as an Enabling Environment

While the group variable of visitor versus resident alone did not have a significant effect on water-based egocentric coherence, the group variable became marginally significant when the regression for water-based egocentric coherence included five other significant independent variables: canal mappability, lake attachment, aquaphilia baseline, age, and income. It is possible that the significant influence of canal mappability on map identifiability led visitors to stay in proximity to canals as spatial anchors from which to navigate unknown territories beyond. Compared to residents, visitors' more frequent transactions with canals may have resulted in more salient memory of landmarks along canals, as captured by the independent variable of water landmark identifiability or the dependent variable of water-based egocentric coherence. The use of canals as water-based spatial anchors for environmental adaptation may be the underlying mechanism of water urbanism as an enabling environment for newcomers.

Water-based egocentric coherence was significantly higher for younger, higher-income participants with a higher level of lake attachment, while age, income, and lake attachment had no significant influence on allocentric coherence measures. This specific population may have more salient images of water landmarks due to their recreational use of waterscapes. Finally, the significant negative relationship between allocentric and egocentric coherence levels and aquaphilia sensitivity baseline can be interpreted as follows. Those with the least sensitivity to water's stress-reducing effect tended to have a more coherent cognitive city image for allocentric and egocentric frames of reference. Those with a less coherent cognitive city image were likely to have a greater water-based comfort as sensitivity to the stress-regulating effects of waterscapes. It is possible that this spatially challenged population tended to seek proximity to waterscapes for stress reduction. This postulated frequent interaction suggests that waterscapes may serve as spatial anchors for those with a higher aquaphilia baseline, helping them to develop a more coherent cognitive city image for environmental adaptation.

4.6. Conclusions

This research demonstrated a possible multi-sited research design for investigating the image of cities through cognitive mapping, photovoice, and emotional recall protocols. It also proposed sketch-map evaluation rubrics that generated reliable coherence measures to study spatial cognitions of an environmental image as a combination of top-down and eye-level views. The salience of canals in a two-dimensional cognitive map is a significant element for the integration of both perspectives associated with a water-city image. The use of canals as water-based spatial anchors to navigate unfamiliar terrains could help make cities more adaptable for visitors and women by facilitating the formation of a more coherent city image.

4.7. Possible Limitations and Future Improvements

Mediation analyses may be conducted to identify which variable mediates the group effects on the sketch-map coherence measures and other potential mediation effects to help fine-tune the results into more discrete design principles. These mediation analyses should include aquaphilia sensitivity baseline as a covariate to control its significant effect on the coherence measures. Most behavioral geographers or environmental psychologists tend to use survey knowledge as an overarching spatial knowledge category for studying spatial abilities (Golledge & Stimson, 1997). In Appleyard's (1970) study, however, none of the spatially dominant maps with survey knowledge were imageable. The 8- and 12-stage rubrics may still need to be deployed for design research projects to provide sufficient morphological nuance between rubric categories to derive meaningful spatial implications for building an empirical theory of imageability. The rubrics should be tested against more water-centric cities with a larger number of raters to make them more robust for multi-sited applications. But the complexity of the sketch-map rubrics may make them difficult for large sample populations to use. Specific categories may be consolidated if no significant difference between them has been found in pilot data to make the rubrics more accessible to a larger group of non-researcher participants. Furthermore, the results presented in this study may be generalizable only to the sample participants or cities because a quasi-random sampling was used in the absence of a theoretical sampling frame. The same research design should be replicated for a greater number of water-centric cities with a more rigorous sampling procedure before regarding the results as a generalizable theory of imageability for water-centric cities. Finally, the research design should also be tested on non-water cities before applying a unified theory of imageability to water-centric and non-water cities.

CHAPTER IV

AQUAPHILIC URBANISM: WATER-BASED SPATIAL ANCHORS AS LOCI OF ATTACHMENT

1. Introduction

1.1. Problem statement

1.1.1. Contemporary relevance of place in an increasingly placeless world

Most phenomenological place researchers, such as Tuan (1977) and Relph (1976), define place as a culturally bounded center of meanings associated with insidedness and historical continuity. Lewicka (2011) questioned the contemporary relevance of this classical definition of place due to a mounting sense of placelessness in today's globalized cities, which are growing in size and density with increasingly mobile and more diverse populations (Beatley, 2005; Relph, 1976; Southworth & Ruggeri, 2010).

1.1.2. An emerging need to aid place-bonding through place-making in globalized cities

Wilson and Baldassare (1996) found a negative correlation between sense of community and its size, density, and ethnic diversity as measures of urbanization. Researchers observed that, compared to home and neighborhood, physical factors were more important reasons than social factors underlying people's attachment to the city (Hidalgo & Hernandez, 2001; Scannell & Gifford, 2010b) as a place beyond a person's social network (Beckley, 2003). These empirical findings suggest an emerging need among social scientists and practitioners in city planning and design to study possible ways to help facilitate place-bonding through place-making in the public realm of globalized cities.

1.1.3. A dearth of empirical evidence linking place-bonding with place-making

Yet, the disproportional emphasis of place research on the human and the process over the physical factors has resulted in little empirical evidence for the theoretical connections between place-making and place-bonding (Lewicka, 2011). Most positivist place researchers define sense of place or place attachment as people-place bonds attributable to both physical and social factors of the environment (Kyle, Graefe, & Manning, 2005; Lewicka, 2011; Scannell & Gifford, 2010a). However, the historic overlap between community and place attachment research (Fried, 1984) may have led to a socially dominant view of the material environment as a stage of shared cultural and behavioral processes, instead of a main subject of study (Gieryn, 2000; Gustafson, 2006; Lewicka, 2011). Likewise, many positivist place researchers have regarded sense of place as a social construction more so than an attitudinal outcome of environmental interactions (Alkon & Traugot, 2008; Greider & Garkovich, 1994; Stokowski, 2002).

1.1.4. Divergent focuses on place-bonding and place-making as disconnected discourses

A number of positivist environmental psychologists have frequently focused on developing methods for measuring place constructs and testing the dimensionality of sense of place (Jorgensen & Stedman, 2001, 2006; Stedman, 2002, 2003b), including place meanings (Davenport & Anderson, 2005; Davenport, Baker, Leahy, & Anderson, 2010; Williams, Watson, & Alessa, 2001), place attachment (Kyle et al., 2005; Raymond, Brown, & Weber, 2010; Williams & Vaske, 2003), and the connectedness to nature (Mayer & Frantz, 2004). To test measurement scales for symbolic meanings or cognitive attachment, most of these researchers often minimized or preselected descriptions of environmental features to generate statements of beliefs or attitudes for evaluation by participants.

In contrast, design-centric place researchers have often followed the urban picturesque tradition to investigate place-bonding through the three dimensions of imageability as place structure, identity, and meaning (Appleyard, 1970; Isaacs, 2000; Lynch, 1960; Ruggeri, 2014). These urban cognition researchers may have provided more ecologically valid place-making implications by allowing participants to select salient environmental features or attributes using visual recall methods, such as cognitive mapping and photovoice. However, this line of place research has not substantiated a generalizable theory to link place-making and place-bonding and has remained largely disconnected from the empirical theories substantiated by quantitative place researchers.

1.2. Background

1.2.1. From specific places to general classes of the physical environment

Over the last decade, there has been a growing interest in attachment to places other than permanent residences (Lewicka, 2011). Many of these emerging loci of attachment have been high-amenity places with bodies of water (Bolund & Hunhammar, 1999; Davenport & Anderson, 2005; Hammitt, Backlund, & Bixler, 2006; Lorenz & Kolb, 2009; Stedman, 2003a). Feldman (1990) speculated that the loci of attachment for an increasingly mobile population are likely to shift from specific places toward general classes of the physical environment, such as water.

1.2.2. Aquaphilia as water-based topophilia

By using environmental attributes to model the dimensions of sense of place as the cause of place attachment and place satisfaction as effects, Stedman (2003a) found lakes to embody the sense of place of a lake-rich landscape due to their intrinsic symbolic meanings. Ogunseitan (2005) validated the influence of water on topophilia, which, as coined by Tuan (1974, p. 93), denotes all human “affective ties with the material environment" developed primarily through the senses as aesthetic responses. The author repurposes aquaphilia here to allude to an instinctual human affection toward water-based spatial anchors as a water-based topophilia or an aquaphilic sense of place.

1.2.3. From aquaphilic sense of place to water-based place attachment

(Mansor & Said, 2008) found that the presence of water along a green infrastructure network and the extent to which the network functioned as a spatial anchor both contributed to residents' attachment to their town. The findings suggest that an aquaphilic sense of place could potentially contribute to a water-based place attachment at the city level. Water-based place attachment depicts the influence of aquaphilia, which is the intrinsic interconnectedness to water-based spatial anchors as material environments, on people's attachment to a water-centric city as a physically, socially, culturally, and economically constructed locus of attachment.

1.2.4. Spatial anchors as loci of the environmental-psychological theory of attachment

Anchor-point theory from behavioral geography (Golledge, 1992; Osmond, 1963) suggests that spatial anchors, which are functionally salient features for orientation, tend to emerge first during spatial memory recall of environmental maps and images. These spatial anchors are likely to be imageable features that provide place identity (as a sense of identifiability) and place dependence (as a sense of orientation) (Lynch, 1960). These urban cognition theories suggest that an environmental-psychological tripartite theory of place attachment based on place identity and place dependence as key dimensions (Kyle et al., 2005; Williams & Vaske, 2003) could possibly help explain the connections between place-making and place-bonding underlying the nature of spatial anchors.

1.2.5. Waterscapes as loci of the social-psychological theory of attachment

As a traditional locus of attachment, home has been found to be the main spatial anchor in cognitive maps (Golledge & Stimson, 1997). Several empirical studies have shown that water bodies tend to be the first elements people draw in their sketch maps (De Jonge, 1962; Lynch, 1960; Milgram, 1976). In fact, newcomers have been found to seek out urban water bodies for environmental self-regulation as a rudimentary form of place attachment because of their resemblance to those in the cities of their previous residences (Proshansky, Fabian, & Kaminoff, 1983). The findings of these studies suggest a social-psychological theory of attachment (Bowlby, 1977; Bretherton, 1992; Douglas, Kearney, & Leatherman, 2000; Holmes, 1993; Zimmer, 1999) may provide promising directions for modeling water-based place attachment. Specifically, water-based place attachment could potentially be predicted by sense of familiarity and comfort attributable to water-based spatial anchors as potentially analogous loci to the salient figures in the social-psychological theory of attachment.

1.3. Study goal and objectives

The ultimate aim of this research was to identify an adequately fitting model for theorizing the relationship between place-making and place-bonding for a variety and number of cities, physical factors, and participants. As a first attempt to tackle this long-term goal, this study focused on the use of water-based measures for testing three theoretically informed alternative models of sense of place as a set of interrelated constructs. To produce these measures, the author employed cognitive mapping, photovoice, and structured questions during 60 semi-structured field interviews in eight water-centric cities. Each model represents an alternative postulate for operationalizing an aquaphilic sense of place as a potential cause of water-based place attachment at the city level.

2. Methods

2.1. Selection of study sites

Lynch (1960) speculated that water-centric cities, such as Venice, the lakefront of Chicago, and Dutch polder cities, were likely to be imageable environments conducive to psychological integration. The Google search engine indicates that 12 cities have been referred to as "the Venice of the North" because they are known for their canals and bridges. Wikipedia provides a list of 10 such cities as follows: Amsterdam, Bruges, Copenhagen, Giethoorn, Hamburg, Henningsvær, Manchester's-Hertogenbosch, Saint Petersburg, and Stockholm. Berlin (MacLean, 2011) and Ghent (Raplee, 2010) have also been considered comparable to Venice. Among this shortlist of alluring water cities, the author selected six as study sites based on precipitation pattern similarity and geographical proximity to minimize sampling costs. The six cities chosen are Amsterdam and Giethoorn in the Netherlands, Ghent and Bruges in Belgium, and Berlin and Hamburg in Germany. Only Amsterdam and Hamburg are coastal water cities while the other four are inland water cities. The author added Rotterdam, the second largest Dutch city, and Almere, the fastest growing city in Europe, to the selection of study sites because, similar to Amsterdam and Hamburg, these two Dutch polder cities are also appealing coastal water cities. As shown in Table 4.1., the final list of study sites comprises four coastal water cities and four inland water cities. This selection of water cities allows for some level of variability in the amounts and types of water features; although all eight water cities have canals, all four coastal water cities have a water density greater than 10% due to the presence of larger water bodies such as harbors and lakes. The water density for the inland cities is less than 10%. The author calculated water density by dividing the total surface of water in each city by its total area of land.

Table 4.1.
Geomorphology and water density of coastal and inland water cities.

Water Bodies	**Coastal Water Towns**				**Inland Water Towns**			
	Almere	Amsterdam	Hamburg	Rotterdam	Berlin	Bruges	Ghent	Giethoorn
Estuary	Yes	Yes	Yes	Yes	No	No	No	No
Harbor	Yes	Yes	Yes	Yes	No	No	No	No
Lake	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Canal/ River	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Water Density	>10%	>10%	>10%	>10%	<10%	<10%	<10%	<10%

2.2. Sampling

As a sampling frame for residents and visitors in these eight cities does not exist, the author randomly sequenced sampling sites to create an approximation of a random sample that could be as representative of a theoretical sampling frame as possible. This theoretical sampling frame assumes it is possible to capture all residents and visitors in each water city. Specifically, the author first used a randomized order to sequence the eight water cities in Table 4.1. and then each city's nine sampling sites, which consisted of major entry points (such as airports, inter-city train stations, and bus stations), hotels, cafes, ethnic stores, universities, city halls, and tourist bureaus. The author chose these sites to conveniently sample a good mix of residents and visitors, high- and low-income populations, experts of environmental design, and non-experts, as well as immigrants and visitors from varying countries of origin. The author allocated five hours of sampling time for each sampling site, adding up to a total of 45 hours for all nine sites in each water city.

2.3. Data collection

Across all eight cities, the investigator recruited a total of 60 participants for semi-structured interviews. As shown in Table 4.2., these interviews included three recall protocols, including cognitive mapping (instruction one), photovoice (instruction two) (questions three and four), and emotional bonding (instruction three), followed by two structured questions (questions three and four) and an open-ended question regarding participants' length of stay (question six). The author coded participants' responses to provide measures for the six variables used by the three competing path analysis models. Section 3 describes the theoretical underpinnings of these three models and six variables.

2.4. Coding plan

To assess the respondents' water-based familiarity, the investigator used a cognitive mapping protocol to prompt them to recall the city as a map and identify five features or locations that came to mind first when imagining drawing a map of the city (instruction one). In addition, to obtain an indicator for water-based place identity, the author engaged each participant in a photovoice exercise to recall five pictures of the city they would use to describe the city to friends who had never been there (instruction two). Furthermore, to quantify water-based place attachment, the investigator asked participants to recall five things they would miss about the physical environment if they had to leave the city the next day (instruction three). For generating three variables from interview items one, two, and three, the investigator assigned 1 or 0 as the base score for each answer with or without water first. Then, the author applied a weight of 5 to the base score for the first answer, 4 for the second answer, and so forth, to account for the significance of the recall sequence.

Table 4.2.
Protocols and interview questions for variable measures.

Variable	Interview Questions and Instructions
Water-based familiarity[a]	1. Imagine you are drawing a map of the city. Please name or describe the five features or locations that come to mind first. Please do not consult a city map.* a) 5 for water /0 for non-water, b) 4/0, c) 3/0, d) 2/0, e) 1/0
Water-based place identity[a]	2. If you were to take pictures of the city to describe it to someone who has never been there, what would you take pictures of? What comes to mind first? What comes next? a) 5 for water /0 for non-water, b) 4/0, c) 3/0, d) 2/0, e) 1/0
Water-based place attachment[a]	3. What are the five things you would miss about the physical environment if you had to leave the city tomorrow? a) 5 for water /0 for non-water, b) 4/0, c) 3/0, d) 2/0, e) 1/0
Water-based comfort[b]	4. How much do the bodies of water in the city help you relax when you are stressed?
Water-based place dependence[b]	5. How much do you use the bodies of water in the city to orient yourself? □ Very much (3) □ Somewhat (2) □ Not at all (1)
Length of Stay[c]	6. How many years/days have you been in this city (altogether)?

[a] Code each answer 1 or 0 based on whether or not it references water or not before assigning a weight from 5 to 1 to account for the sequence of recall. Use a weighted average to create variable measure.
[b] Use Likert scale to generate scores for responses along the gradient offered.
[c] Convert response to number of days, center on the average, and divide by the average

As shown in the following formula, the investigator calculated an average from the sum of all five weighted base scores to derive measures for water-based familiarity from the cognitive mapping protocol results, water-based place identity from the photovoice exercise responses, and water-based place attachment from the five responses to question three:

$$\text{Weighted average} = (5 * \text{first answer base score} + 4 * \text{second answer base score} + 3 * \text{third answer base score} + 2 * \text{fourth answer base score} + 1 * \text{fifth answer base score})/5$$

To ordinate the score for water-based comfort, the author asked the participants to use a three-point Likert scale to assess the extent to which the water bodies in the city helped them relax when stressed (question four). The investigator used the same Likert scale to assess water-based place dependence by asking participants the degree to which these water bodies helped them orient themselves (question five). To control for participants' level of assimilation, the author asked how long residents had dwelled in the city of residence or how long visitors had been visiting the host city (question six). In order to derive the indicator for length of stay, all responses were normalized—that is, converted to the number of days, centered on the average, and divided by the average. Please refer to Sections 3 and 4 for justifications of these measures and coding schemes.

2.5. Data analysis

2.5.1. Path analysis

The author conducted path analysis to model complex multivariate relationships between a number of variables as interactions or directed dependencies. Path analysis provides simultaneous estimations of regression weights for a set of multiple linear regression models with a focus on causalities. In addition, path analysis is a specific type of structural equation modeling (Stokman) technique (Musil, Jones, & Warner, 1998): Most SEM models combine factor analysis and regression models by using both latent and manifest variables. In contrast, a path analysis model is composed of only manifest variables with regression weights as path coefficients. As a form of SEM, path analysis employs a maximum likelihood estimation procedure that assumes multivariate normality.

2.5.2. Multivariate normality

Table 4.3. indicates that five participants had missing data for length of stay, while three participants' data were missing for water-based comfort and water-based place dependence. Before including their responses in the path analysis along with the other participants' complete data, the author conducted data screening to test the assumption of multivariate normality and verify whether these participants' omitted measures were missing completely at random. SPSS provided the values and standard errors for skewness and kurtosis to test for the assumption of multivariate normality. Their z scores were calculated via dividing their values by standard errors. As shown in Table 4.3., with the exception of length of stay, the assumption of multivariate normality was not violated for the structural variables because the absolute values for their skewness and kurtosis z scores were less than 3 (Tabachnick & Fidell, 2001, pp. 79-81).

2.5.3. Data missing completely at random

To confirm whether there was a systematic pattern for the missing data, the author employed SAS (statistical analysis software) version 8.2 to run a macro for Little's missing completely at random (MCAR) test (Appendix G). The MCAR test result indicated that missing values were randomly distributed across all observations and missingness was not dependent on observed values in the data (p=0.92>.05). Regardless of the missing data, the author estimated the path analysis model using results from all 60 interviews with full information maximum likelihood (FIML) in IBM® SPSS® Amos 22.0. Amos is a trademark of Amos Development Corporation. FIML used all the information from the observed data. The mean and variance for missing portions of a variable were estimated based on the observed portions of other variables in the covariance matrix (Marcus & Sarkissian, 1988).

Table 4.3.
Descriptive statistics, including skewness and kurtosis.

Path Analysis Variables	N	Min.	Max.	Mean	Standard Deviation	Skewness Z Score	Kurtosis Z Score
Water-Based Familiarity	60	0.00	15.00	6.57	4.02	0.23	-1.44
Water-Based Place Identity	60	0.00	15.00	4.737	4.14	1.90	-1.11
Water-Based Place Attachment	60	0.00	13.00	3.82	3.75	2.45	-0.31
Water-Based Comfort	57	1.00	4.00	2.18	0.85	-0.53	-1.98
Water-Based Place Dependence	57	1.00	3.00	2.11	0.80	-0.59	-2.23
Length of Stay (Centered)	55	-1.00	5.39	-0.00	1.58	5.56	4.13

3. Theory

3.1. The social-psychological (SP) model of attachment

Many social psychologists define attachment primarily as a cross-cultural behavior of proximity-maintenance, that is, the desire to be near salient figures we are attached to because they provide us with security and comfort in the face of threats and environmental stressors (Bowlby, 1977; Bretherton, 1992; Douglas, Kearney, & Leatherman, 2000; Holmes, 1993; Zimmer, 1999). Similarly, some design or planningcentric researchers and geographers apply this model toward place, as opposed to person, as the locus of attachment, by describing attachment as "an affective bond that people establish with specific areas where they prefer to remain and where they feel comfortable and safe" (Hernández, Carmen Hidalgo, Salazar-Laplace, & Hess, 2007). Fig. 4.1. shows a theoretical specification of an interpersonal attachment model for place attachment of the first type above based on the assumption that a sense of familiarity provides emotional security (Lynch, 1960). This sense of familiarity can promote a sense of comfort and facilitate place attachment as people approach a place for environmental self-regulation, such as relief from stress.

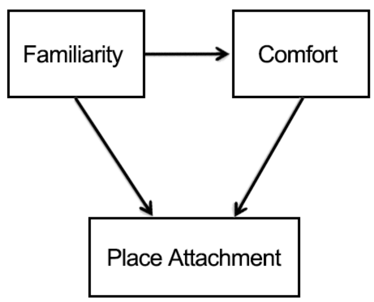


Fig. 4.1. The social-psychological (SP) model of attachment.

3.2. The environmental-psychological (EP) model of attachment

Jorgensen and Stedman (2001, 2006) validated a tripartite model of attitudes (Fig. 4.2.) proposed by Rosenberg and Hovland (1960) with the following three related place dimensions: cognitive (place identity), behavioral (place dependence), and emotional (place attachment). Although their model considers potential two-way interactions between any two of these three constructs, many other validated models attribute place attachment to both place identity and place dependence (Bricker & Kerstetter, 2000; Kyle, Graefe, Manning, & Bacon, 2004; Moore & Graefe, 1994; Ning Chris, 2012;

Williams & Roggenbuck, 1989; Williams & Vaske, 2003). Whereas most researchers have found theoretical, empirical, and applied distinctions between place identity and dependence, Nicholls and Cazenave (2010) pointed out the influence of place dependence on place identity.

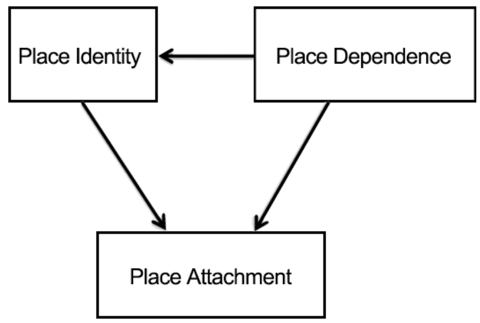


Fig. 4.2. The environmental-psychological (EP) model of attachment.

3.3. The social-environmental-psychological (SEP) model of attachment

The diverse array of place attachment models appears to result from the use of different terms and definitions for place attachment. Advocates of the EP model posit place attachment as the people-place emotional bond sourced from place identity and place dependence (Bricker & Kerstetter, 2000; Kyle et al., 2004; Moore & Graefe, 1994; Ning Chris, 2012; Williams & Roggenbuck, 1989; Williams & Vaske, 2003). Other environmental psychologists postulate emotional bonding—a narrower conception of place attachment—as an emotional dimension within sense of place – a broader construct for place attachment (Jorgensen & Stedman, 2001; Stedman, 2003). This wider construct of place attachment as sense of place is posited to involve a tripartite process with affective, cognitive and behavioral dimensions; these three dimensions of sense of place appear to correspond to a narrow conception of place attachment as emotional bonding, place identity, and place dependence respectively (Harmon, 2005; Scannell & Gifford, 2010). This view of place attachment as a wider sense of place construct suggests proximity-maintaining to place, that is, social psychologists' narrower definition of place attachment, a behavioral dimension of sense of place, which is a broader conception of place attachment (Jorgensen & Stedman, 2001; Scannell & Gifford, 2010). Proximity-maintenance—a behavioral dimension of place attachment as sense of place—has been equated with place dependence, which Stokols and Shumaker define as a goal-affordance aspect of sense of place (Bolund & Hunhammar, 1999; Lorenz & Kolb, 2009; Stokols & Shumaker, 1981).

To reconcile diverging definitions and terms associated with place attachment, this study replaces proximity-maintenance, indicated as place attachment in the SP model (Fig. 4.1.), with place dependence in the EP model (Fig. 4.2.) to propose a social-environmental-psychological (SEP) model (Fig. 4.3.).

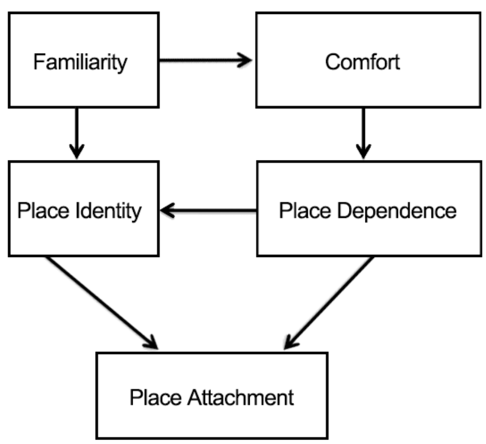


Fig. 4.3. The social-environmental-psychological (SEP) model of Attachment.

This composite model hypothesizes that proximity-maintenance, social psychologists' narrower definition of place attachment in the SP model, equates with a behavioral dimension of sense of place, which is also referred to as place dependence in the EP model. The SEP model uses this common ground between the SP and EP models to generate their composite, and postulates emotional bonding, that is, the narrower conception of place attachment, as an affective dimension of sense of place (Scannell & Gifford, 2010) in the composite model. These three models were empirically tested by focusing on the contributions of water to each construct.

3.4. Adapting SP, EP, and SEP models for a topophilic sense of place

Kaplan (1984) defines a topophilic sense of place as what makes it easy to attach oneself to a novel place because the place seems familiar and provides psychological comfort. Similar to the SP model, this definition implicates sense of familiarity and sense of comfort as two potential contributors to a sense of place that evokes topophilia. In line with the EP model, Kaplan (1984) also points out sense of place as the extent to which a place's physical aspects influence its legibility as a cognitive map, make environmental features identifiable, and facilitate goal affordance as the compatibility between environmental affordance and human purposes. These three physical aspects of sense of place appear to describe narrower conceptions of familiarity, place identity, and place dependence in the absence of non-physical influences. For example, the legibility and identifiability of environmental features in cognitive maps and eye-level recall images are akin to the narrower aspects of familiarity and place identity, although these two constructs are also attributable to non-physical factors that include cultural meanings, social affordance, and past memories.

Kaplan's (1981) interpretation of goal affordance from the perspective of fulfilling human purposes remains a rather elusive goal because the development of social life and human happiness is an optimal condition that is significantly afforded by an ideal public realm (Southworth, Cranz, Lindsay, & Morhayim, 2012). In contrast, goal affordance from the standpoint of wayfinding can be as simple as enabling individuals to orient themselves with ease through maintaining proximity to environmental features as navigation aids.

In this study, goal affordance in relation to self-orientation through the maintenance of proximity to salient features appears as the common ground between the SP and EP models. Sense of orientation as one important "human purpose" refers to the extent to which people rely on certain physical aspects of a public realm to find their way with ease. It is proposed as a measure for capturing the physical aspect of place dependence in this study. The SEP model appears to account for all the aforementioned constructs of a topophilic sense of place based on a functional view of environmental aesthetics in the context of wayfinding. Fig. 4.4. shows how the SP, EP, and SEP models described earlier in Section 3 are adapted for operationalizing an aquaphilic sense of place as water-based familiarity, comfort, place dependence, and place identity.

3.5. Adapting SP, EP, and SEP models for an aquaphilic sense of place

While the existence of idiosyncratic preferences has challenged the legitimacy of universal aesthetics, evolutionary biology has provided some support to certain universal aesthetics related to human preferences for survival-enabling habitats (Carlson, Engebretson, & Chamberlain, 2006). Such life-inducing environments are often characterized by the presence of water, food, and defense advantages (Ulrich, 1993). This particular "functionalist" approach to aesthetics in the public realm is commonly described as biophilia, that is, the innate human liking of life-inducing environments that facilitate survival and wellbeing (Kellert, 1995). The author postulates aquaphilia as an essential major sub-dimension of biophilia because almost all historic human settlements originate from sources of water or areas in proximity to surface waters due in part to this aesthetic preference. These water-based environments are also often associated with greater water, food, and defense advantages than places with very few surface water features. This functional approach to public realm aesthetics suggests that aquaphilia may be associated with a water-based sense of place conducive to survival and wellbeing. Aquaphilia may thus be conceptualized as a subset of a biophilia-based topophilia attributable to the presence of water features.

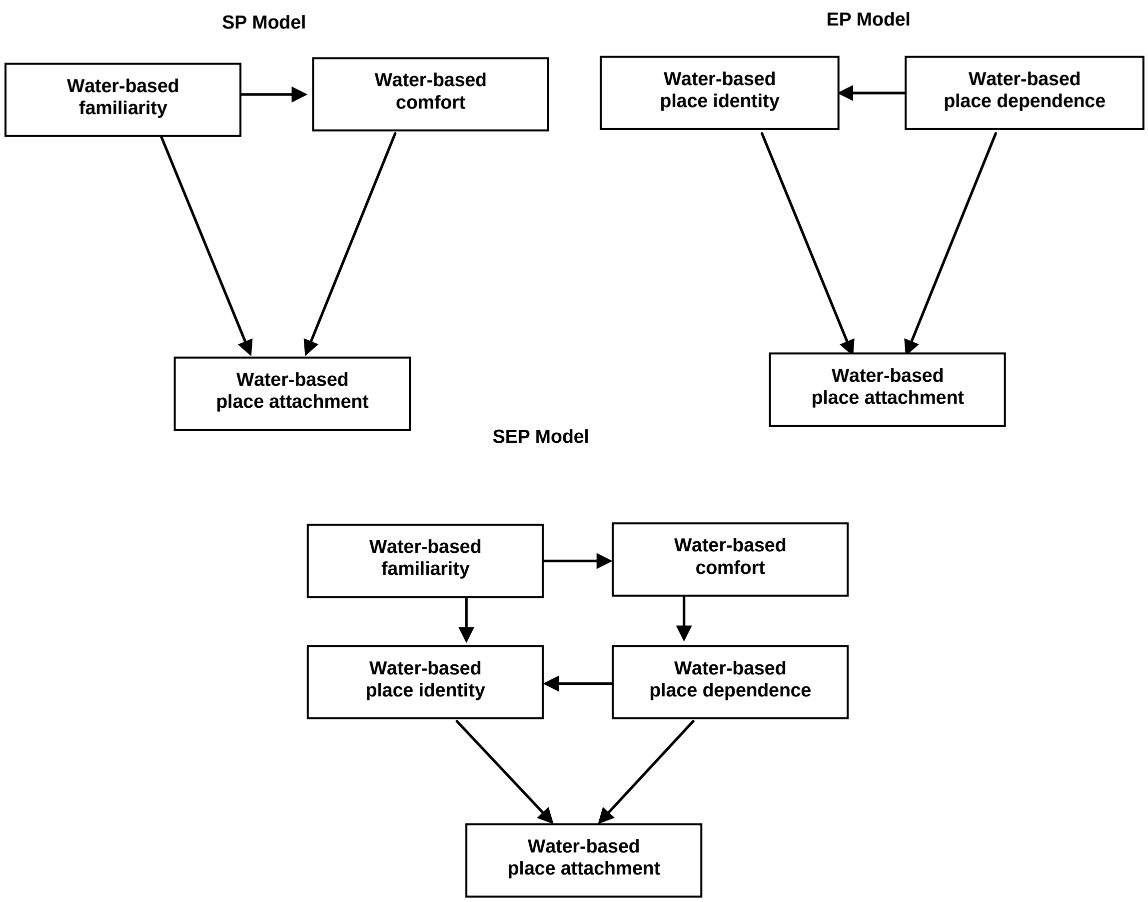


Fig. 4.4. The SP, EP, and SEP models of an aquaphilic sense of place.

4. Results

4.1. Model comparisons

Fig. 4.5. shows a base model for testing the SP, EP, and SEP models as nested models. Model testing results can be found in Appendix H. A base model incorporates the paths from all nested models, each of which can be derived from the base model by making irrelevant paths zero.

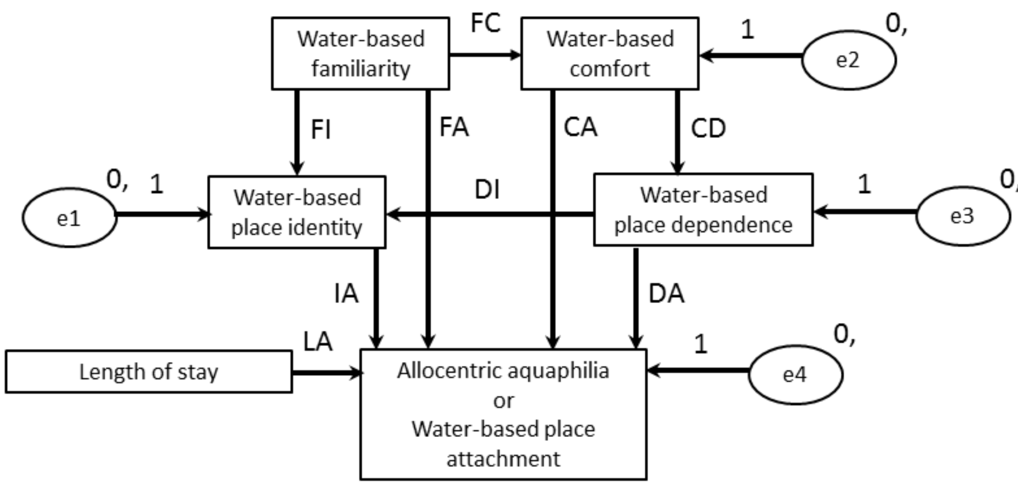


Fig. 4.5. Base model for nesting SP, EP, and SEP models of an aquaphilic sense of place.

The regression weights of the following paths are set to zero to create a nested model for the SP model (to isolate Fig. 4.1.) because they only apply to the other two EP or SEP models: FI (water-based familiarity and water-based place identity), CD (water-based comfort and water-based place dependence), IA (water-based place identity and water-based place attachment), DA (water-based place dependence and water-based place attachment), and DI (water-based place dependence and water-based place identity). Similarly, the EP model (that isolates Fig. 4.2.) assigns zero to the regression weights of five paths as follows: FI (water-based familiarity and water-based place identity), FC (water-based familiarity and water-based comfort), CD (water-based comfort and water-based place dependence), FA (water-based familiarity and water-based place attachment), and CA (water-based comfort and water-based place attachment). The SEP model (Fig. 4.3.) assumes zero for the regression weights of paths FA (water-based familiarity and water-based place attachment) and CA (water-based comfort and water-based place attachment) because they do not apply to the SEP model.

Since length of stay violated the assumption of multivariate normality, the author tested these nested models both with and without length of stay to identify possible problematic effects from including this parameter in the model. The SP model path analysis did not have adequate fit with ($p=.00<.05$) or without length of stay ($p=.00<.05$). There was also a lack of adequate fit for the EP model with ($p=.00<.05$) or without length of stay ($p=.00<.05$). The SEP model had an adequate goodness of fit with ($p=.89>.05$) and without length of stay ($p=.94>.05$). The investigator also conducted a data driven model testing process to attempt many model forms across the constructs measured. As the three models reported in this paper are those that worked the best and had a basis in the literature, the author tested them as nested models to identify the best-fitting model.

4.2. Power analysis

As length of stay appeared to have improved the model fit, it was therefore always included. As shown in Appendix I, the author conducted a power analysis to test whether the sample size was sufficient (N=60) for comparing the SP, EP, and SEP nested models with length of stay included. To compare each pair of nested models, the investigator used an online calculator to compute power (d) in order to determine whether there was adequate power (d=.8) based on a significance level of 5%, and each model’s root mean square error of approximation (RMSEA). RMSEA is one of the fit indices generated in AMOS 22.0 (Preacher & Coffman, 2006). The power analysis result shows that the sample size (N=60) provided adequate power for claiming the SEP model as a significantly better-fitting model than the SP ($d=.99>.8$, $\alpha=.05$) or EP model ($d=.98>.8$, $\alpha=.05$).

According to Bentler and Chou (2012), the ratio of sample size to the number of free parameters for SEM research is 5:1. This suggests that the minimum sample size for this study should be 55, given that there are 11 free parameters (seven paths and four error terms) to be estimated. In the case of multiple linear regressions, as researchers typically use the number of variables to calculate the ratio, the minimum sample size can be reduced to 30 for 6 variables instead of 11. This supports the assumption that this study provides an adequate sample size for comparing the goodness of fit of the three proposed models.

4.3. Path analysis

As the SEP model is the only adequately fitting model, and thus the best-fitting alternative based on the nested-model testing results in Section 4.1, this section only reports the path analysis outcome for the SEP model. All path analysis results can be found in Appendix J. Fig. 4.6. shows the standardized beta path coefficients of the SEP model with length of stay as a control variable. As the endogenous variables are also affected by factors outside the model (including measurement error), the effects of these extraneous variables are depicted by the error terms (e1, e2, e3, and e4) in the model. Path analysis indicates that the SEP model provided adequate fit to the data ($\chi2$ (8)=3.589, $p=.892$, CFI=1.00, RMSEA=.000; $\chi2/df=.449$): The Chi-Square minimization was non-significant; the comparative fit index (CFI) was above .90; the Chi-square Ratio ($\chi2$/df) was below 2.0; and the root mean square error or approximation was below .08 (Bentler & Chou, 1987; McDonald & Ho, 2002). As indicated by the R^2 values within Fig. 4.6., the SEP model explains 11% of the variance in water-based comfort, 14% of the variance in water-based place dependence, 28% of the variance in water-based place identity, and 35% of the variance in water-based place attachment.

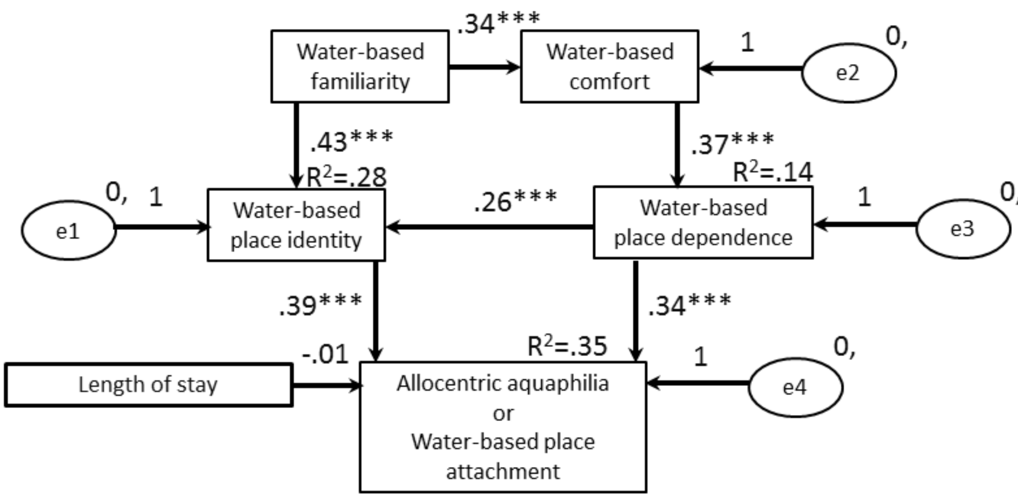


Fig. 4.6. Test of composite model (SEP model, N=60) with Length of Stay (Centered). Model fit: $\chi2$ (8) = 3.589, p = .892, CFI = 1.00, RMSEA = .000; $\chi2$/df = .449. Paths are shown as standardized beta path coefficients. ***p < .001, **p < .01, *p < .05

The regression weights for the best model (SEP model) in Fig. 4.6., as opposed to those for all the rejected inferior models, indicate the following:

1) water-based familiarity is significantly associated with water-based comfort (β=.34, p<.01);
2) water-based familiarity is significantly related to water-based place identity (β=.43, p<.001);

3) water-based comfort is significantly associated with water-based place dependence (β=.37, p<.01);

4) water-based place dependence is significantly related to water-based place identity (β=.26, p<.05);

5) water-based place dependence is significantly correlated with water-based place attachment (β=.34, p<.01);

6) water-based place identity significantly explains water-based place attachment (β=.39, p<.001); and

7) length of stay does not significantly explain water-based place attachment (β=-.01, p=n.s.).

These interrelationships at varying significance levels and their regression weights are interpreted in the next section with their potential implications for connecting place-making with place attachment.

5. Discussions

5.1. Interpretations of regression weights

The regression weights from the SEP model suggest the following:

1) Water-based familiarity is significantly associated with water-based comfort (β=.34, p<.01): The extent to which waterscapes serve as spatial anchors in a cognitive map could be associated with aquaphilia sensitivity baseline as the level to which water is stress-reducing to a participant. Waterscapes may help enable people to become used to a city more easily, in particular for those more affected by the stress of urban living or more responsive to water's stress-regulating effect. This is possibly because waterscapes are more likely to be salient spatial anchors for this population.

2) Water-based familiarity is significantly related to water-based place identity ($\beta = .43$, $p < .001$): Survey and landmark knowledge related to water features acquired from the allocentric (two-dimensional map-like) and egocentric (eye-level) frames of reference are potentially mutually supportive. The more waterscapes anchor a participant's cognitive map from an allocentric perspective, the more they make scenes identifiable from an egocentric frame of reference. Conversely, the more salient waterscapes are to pedestrians' eye-level experience, the higher-order they are as spatial anchors in their cognitive map.

3) Water-based comfort is significantly associated with water-based place dependence ($\beta = .37$, $p < .01$): waterscapes may help provide a sense of orientation to a greater extent for urbanites with a more sensitive aquaphilia baseline and a higher degree of reliance on water for stress-regulation compared to those more resilient to stress from urban living or less sensitive to water's stress-reducing influence. An alternative interpretation could be that stress reduction due to exposure to waterscapes may enhance one's sense of orientation.

4) Water-based place dependence is significantly related to water-based place identity ($\beta = .26$, $p < .05$): The more waterscapes contribute to a sense of orientation, the more they provide a sense of identifiability as landmarks. The more salient waterscapes are as landmarks, the more likely they are to help people orient themselves.

5) Water-based place dependence is significantly correlated with water-based place attachment ($\beta = .34$, $p < .01$): The degree to which people use waterscapes for self-orientation is likely to be linked to the extent to which people are attached to waterscapes in the public realm and the extent to which these waterscapes contribute to place

attachment at the city level. In contrast, the more people are attached to water features in the public realm or the more waterscapes contribute to city-level place attachment, the more people rely on those water features to orient themselves.

6) Water-based place identity significantly explains water-based place attachment (β=.39, p<.001): The more identifiable waterscapes are as landmarks, the more they become loci of attachment in the public realm and contribute to people's attachment to a city. The level of emotional attachment to waterscapes or their contribution to place attachment at the city level is associated with the degree of salience to which these waterscapes function as spatial anchors to contribute to people's attachment to a city.

7) Length of stay likely does not significantly explain water-based place attachment (β=-.01, p=n.s.): Regardless of their length of exposure to a city, the attachment of residents, newcomers, and visitors to a city can be attributed to an aquaphilic sense of place composed of water-based familiarity, comfort, orientation, and identifiability.

5.2. Interpretations of regression weights and significance level comparisons

Regardless of participants' length of stay, the most significant relationship was found between water-based familiarity and water-based place identity (β=.43, p<.001), as well as between water-based place identity and water-based place attachment (β=.39, p<.001); moderately significant relationships were discerned between water-based familiarity and water-based comfort (β=.34, p<.01), water-based comfort and water-based place dependence (β=.37, p<.01), and water-based place dependence and water-based place attachment (β=.34, p<.01). Water-based place dependence and water-based place identity had the least significant relationship (β=.26, p<.05). These interrelationships of varying significance levels and regression weights may indicate the following:

1) Compared to water-based place dependence (β=.34, $p<.01$), water-based place identity (β=.39, $p<.001$) explains slightly more variance in water-based place attachment at a greater level of significance. Although the difference in significance level could be due to the use of the same weighted average coding scheme for water-based place identity and water-based place attachment, their slight difference in regression weights indicates that water-based place identity (the outcome of water-based imageability) and water-based place dependence (the result of water-based goal affordance) may be equally important contributors of water-based place attachment;

2) Compared to water-based place dependence (β=.26, $p<.05$), water-based familiarity (β=.43, $p<.001$) explains much more variance in water-based place identity at a higher significance level. The differences in significance levels and regression weights appear to suggest either a potential confounding effect from the use of the same weighted average coding scheme for water-based familiarity and water-based place identity or the presence of water-based imageability as their shared underlying higher-order construct.

3) The effect of water-based familiarity on water-based comfort is .34 while controlling all other variables (β=.34, $p<.01$). Since all variables are standardized to be the same as Pearson's r, this regression weight is also a partial Pearson's r between water-based familiarity and water-based comfort. Factor analysis' item-to-total correlations are typically judged satisfactory when their Pearson's r values are greater than .3. Although the author did not conduct a factor analysis, the regression weight for the significant path between water-based familiarity and water-based comfort could suggest water-based spatial anchor as a potential higher-order construct for these two variables. Since the sample size is not large enough for performing a factor analysis, principal components

analysis may be conducted in the future to test whether these two variables could potentially be reduced into a composite variable called water-based spatial anchor. In this hypothesized reduced model, water-based spatial anchor serves as a potential contributor to both a water-based sense of orientation and a water-based sense of identifiability, which are measures of water-based place dependence and water-based place identity.

4) Similarly, the regression weights are greater than .3 for the paths between water-based familiarity and water-based place identity (β=.43, p<.001), as well as water-based comfort and water-based place dependence (β=.37, p<.01). This indicates water-based imageability and water-based goal affordance may be possible higher-order constructs. Future principal components analysis may be performed to confirm whether water-based imageability and water-based goal affordance are possible composite variables for water-based familiarity and water-based place identity and water-based comfort and water-based place dependence respectively. However, water-based imageability may be a stronger construct than water-based goal affordance, explaining the higher level of significance for the path between water-based familiarity and water-based place identity compared to the path between water-based comfort and water-based place dependence. Although the former pair (p<.001) uses the weighted average coding scheme and the latter pair (p<.01) uses the three-point Likert scale, the latter pair has only a moderate level of significance. In contrast to the discussions above for item 2, a shared coding scheme may not be associated with a higher level of significance. Therefore, the difference in coding schemes may not be a significant source of a potential confounding effect.

5.3. Possible improvements

This dataset could be analyzed using group-invariant testing of path coefficients between two randomly split subsamples to verify construct validity and data validity. Another similar test could be conducted between high (coastal) and low (inland) water cities to see if path coefficients differ significantly between these two city categories. If so, it may be necessary to include a group variable of high and low water cities in the model reported here. The model fit may be improved by consolidating measures for higher-order constructs such as water-based imageability, water-based goal affordance, and water-based spatial anchor. These constructs may be used to study their effects on mediating the effect of the city type group variable of high or low water cities on water-based place attachment. Since the author also asked participants to provide reasons for each response, a content analysis of these reasons may provide specific environmental attributes or features for generating statements of beliefs and attitudes as possible scales for testing with a larger sample using exploratory factor analysis in the future. In addition, generating water-based and non-water-based measures from participants' responses could potentially help compare the relative contributions of water-based and non-water-based features to the model constructs and explore the feasibility of using this model beyond water-centric environments.

6. Conclusions

Although the results of this study are limited to a subset of water-centric cities, they help fill the knowledge gap in relating place-making with place-bonding. More precisely, this study lends some preliminary evidence to support a composite model of place attachment (the SEP model) as better fitting than the two tripartite models of attachment postulated from social and environmental psychology literature (the SP and EP models). By focusing on water as one physical aspect of the public realm, this best fitting model (SEP model) operationalizes water-based place attachment as an effect caused by an aquaphilic sense of place based on four possible constructs that are interrelated in a specific way with certain stronger and weaker relationships—water-based familiarity, water-based comfort, water-based place dependence, and water-based place identity.

Akin to the role of primary care takers for infants and toddlers, water-based spatial anchors can evidently help provide a sense of familiarity and regulate stress associated with exploring and coping with unfamiliar environments. Once secure connections with primary caretakers have been established, teenagers and adults are able to take risks and depend on new salient people to help them navigate through the unknown domains beyond home. They ultimately develop emotional attachment to both primary caretakers and these new salient figures (Sommer, 1974). Likewise, aquaphilia—emotional attachment to water in the public realm—may be attributed to both functional and cognitive attachment. The former may be interpreted as seeking proximity to water-based spatial anchors as secure bases for environmental self-regulation and self-orientation, while the latter possibly entails recognition of water bodies as identifiable landmarks for making sense of the unfamiliar territories beyond the immediate surroundings of water-based spatial anchors. A public realm composed substantially of well-designed water elements could potentially facilitate attachment for all people, including newcomers, visitors, and particularly those more susceptible to the stress from urban living.

CHAPTER V

AQUAPHILIA: THE FUNCTION OF AQUAPHILIC URBANISM FOR ADAPTATION

1. Introduction

1.1. Topophilia, biophilia, greening, and green urbanism

Ogunseitan (2005) found that the presence of nature and water significantly contributes to topophilia, which Tuan (1974, p. 93) defines as human "affective ties with the material environment." Building upon Kaplan's (1995) view of biophilia as the underlying mechanism of greening behaviors, Stedman and Ingalls (2013, p. 137) stated that the intersection of biophilia and topophilia could potentially motivate greening behaviors as "collective attempts to restore nature in places that serve as loci of attachment." This greening movement provides a possible self-organizing bottom-up momentum for retrofitting cities with green urbanism for climate mitigation by offsetting carbon dioxide emissions.

1.2. Biophilic urbanism and the biophilia hypothesis

In fact, one of the most prominent theories of green urbanism is Beatley's (2009, 2011) biophilic urbanism, which is largely premised on Wilson's (1984) behaviorist and Kellert's structuralist views of biophilia. Kellert (2012) argued that a biophilic genetic tendency in human nature can diminish or grow due to human interactions with inhibiting or motivating structural forces. Kellert (1995, p. 20) proposed the biophilia hypothesis, which asserts an "all-encompassing form of attachment to life and lifelike processes," including human desires for “esthetic, intellectual, cognitive, and even spiritual meaning and satisfaction.”

1.3. Topophilia, aquaphilia, water retention, and water-coherent urbanism

In this study, the author refers to water-coherent urbanism as an urban design approach centered on the concept of “living with water” harmoniously to make cities psychologically more supportive and more coherent environmentally, economically, and socially. This approach is diametrically opposed to water-resistant urbanism, which the author uses to denote a prevalent fight-or-flight urban design approach to life-threatening water to quickly keep it out of sight and out of mind. Increasing water-retention within green infrastructure systems has been proposed by Beatley and Newman (2013) as the primary pathway through which biophilic urbanism contributes to climate change mitigation and adaptation. This climate-induced water-coherent impetus within the movement of biophilic urbanism may have helped encourage stream-daylighting in cities and provide momentum to the ongoing shift from water-resistant to water-coherent urbanism (Beatley & Newman, 2013); however, most of these stream daylighting projects remain quite limited and largely linear rather than networked, and extensive water retention has often been built and discussed in technical instead of aesthetic terms.

Lynch (1960) postulated that water-centric cities, such as Venice and Dutch polder cities, are likely to be imageable environments and that polder cities tend to have a unifying structure connecting identifiable parts. Lynch (1960) also speculated that the aesthetic coherence of city image tends to help enhance people’s emotional coherence with their cities. By defining aquaphilia as the instinctual human attachment to clean and safe water and waterscapes, the author uses the term aquaphilic urbanism to depict the enhancement of cities' aesthetic coherence through a systematic integration of urban fabrics with waterscapes as loci of attachment. The author postulates that such a water-based sense of place facilitates the development of people's emotional coherence with water-centric cities as the structuralist influence of aquaphilia on topophilia, or water-based place attachment, to help increase people's openness toward water-coherent urbanism.

1.4. Design as a potential mediator of the effect of water density on structuralist aquaphilia

A higher water amenity density has been found to be significantly associated with a higher population growth in the presence of other favorable amenity-related and socioeconomic variables as controls (Deller, Tsai, Marcouiller, & English, 2001). This finding suggests that, with all other variables controlled, compared with inland and upstream cities, the structuralist influence of aquaphilia may be stronger in coastal and downstream cities because their watershed locations tend to be associated with higher water densities. At the same time, for climate change adaptation, emergency flood retention in forms consistent with water-coherent urbanism has been considered more cost-effective when implemented upstream rather than downstream (Hartmann, 2010). No study has investigated whether or how aquaphilic urbanism may mediate the effect of watershed location or water density on the structuralist influence of aquaphilia as one possible motivating force for introducing water-coherent urbanism for public acceptance.

1.5. Study goal and objectives

The overarching goal of this study was to demonstrate the feasibility of a mixed-methods research design for studying whether and how aquaphilic urbanism may help mainstream water-coherent urbanism in upstream and inland cities. The research intended to investigate how water amenity density or watershed location may not determine the structuralist influence of aquaphilia on the acquired human attachment to a water-centric environment. For city-level adaptation, the study aimed to reveal the potential of the structuralist influence of aquaphilia, as the aesthetic appeal of water-centric urban environments, to help introduce water-coherent urbanism to upstream and inland cities for public acceptance. At the individual level, this study explored how waterscape attributes facilitated environmental adaptation to help derive possible evidence-based design guidelines of aquaphilic urbanism.

1.6. Project significance

Overall, the findings suggest that aquaphilic urbanism can encourage the use of water-coherent urbanism for retrofitting cities to facilitate environmental adaptation. One possible long-term impact of this observation is that when water-coherent urbanism becomes systematically integrated into upstream and inland cities at a watershed scale, it may aid these cities to more attractively better cope with urban flooding and to mitigate their contributions to downstream flooding.

1.7. Theory and calculations

1.7.1. Water-based imageability

Although water-based imageability has been discussed in some empirical studies due to the salience of water elements in cognitive maps, the environmental image often involves two frames of reference—a top-down map-like and eye-level photograph-like perspective. These two facets of spatial schemas are widely discussed as allocentric and egocentric frames of references by neuroscientists (Klatzky, 1998; Mou, McNamara, Valiquette, & Rump, 2004). These perceptions seem to correspond to two components of imageability proposed by Lynch (1960a): structure and identity. Structure is similar to the mappability-based legibility, and identity is akin to the identifiability of environmental features, as described in Kaplan's (1984) functional view of aesthetics. The author postulates that these two perspectives of water-imageability can be conceptualized as a water-based familiarity, or a sense of familiarity attributable to water, and a water-based place identity in the sense of water's influence on a place's identifiability.

1.7.2. Water-based goal affordance

Kaplan (1984) refers to goal affordance as a human-environment fit for the satisfaction of goals and needs or the compatibility between environment and human purposes. Stress reduction has been found to improve people's sense of orientation (Brunyé, Mahoney, Augustyn, & Taylor, 2009) and may provide a sense of comfort to aid a sense of orientation, which is associated with people's emotional coherence with the environment (Lynch, 1960). Furthermore, the use of the environment to adjust the physiological self is a form of environmental self-regulation (Korpela, Hartig, Kaiser, & Fuhrer, 2001), which is related to topophilia (Korpela, 1989). The author posits that water-based goal affordance can be composed of water-based comfort as water's contribution to stress regulation, and water-based place dependence as water's contribution to people's ability to self-orient in a water-centric city.

1.7.3. Contributions of water-based imageability and goal affordance to aquaphilia

In the context of wayfinding for water-centric cities, the author refers to water-based imageability as emotional attachment and to water-based goal affordance as functional attachment. The author also refers to allocentric aquaphilia as the structuralist influence of aquaphilia on topophilia, which is a water-based place attachment at the city level. Some researchers substantiated that topophilia, or sense of place, can be attributed to both symbolic and functional attachments (Williams, Patterson, Roggenbuck, & Watson, 1992; Williams & Roggenbuck, 1989). The author postulates that both water-based imageability and water-based goal affordance contribute to allocentric aquaphilia.

1.7.4. Allocentric aquaphilia and people's openness toward water-coherent urbanism

Nicholls and Cazenave (2010) found that functional attachment influences emotional attachment, which encourages environmentally responsible behavior. These findings support the hypothesis that water-based goal affordance influences water-based imageability, which contributes to people's openness toward water-coherent urbanism; however, it is unclear whether allocentric aquaphilia is an indispensable nexus between water-based imageability and water-coherent urbanism.

1.7.5. Accounting for individual factors with aquaphilia sensitivity baseline

Despite aquaphilia's ostensibly universal nature due to its partial genetic influence (Coss, 1990), a water-centric environment does not necessarily reduce stress in all cases. Water-based comfort, or water's contributions to stress reduction, may double as an aquaphilia sensitivity baseline to account for the influences of water's aesthetic or salutogenic quality on aquaphilia. People's preferences have been found to change depending on the quality of water, such as clarity and color, as well as its general environs (Davies-Colley & Smith, 2001; Maslow & Lewis, 1987; Newman, 1972). People's varying psycho-physiological baseline states may also lead to individual differences in environmental stress responses related to water in landscapes (LaRue, 1974; Newman, 1973). It is possible that these individual and contextual differences may result in varying perceptions of water's restorative aesthetics. Moreover, aquaphobia could potentially be induced by past traumatic events related to drowning (Sommer, 1967) or flood-induced property damage (El-Sharkawy, 1979). Aquaphilia may also be affected in human perceptions via cultural, political, economic, and social factors.

1.7.6. Accounting for environmental factors with waterscape variables

Waterscapes were differentiated into water landmarks, which are salient features along or across water, canals, lakes, rivers, and harbors, because they roughly correspond to Lynch’s (1960) five elements of imageability, which are landmarks, paths, nodes, edges, and districts. For each of the five waterscape types, mappability, identifiability, and attachment were proposed as indicators for Lynch’s (1960) cognitive components of imageability, namely, structure, identity, and meaning.

1.7.7. Investigating water-based familiarity with cognitive mapping recall

Golledge (1992) stated that spatial anchors contribute to spatial familiarity, which he defines as an ability to identify and locate features in addition to relating the them to other features in spatial memory. Spatial anchors are predisposed to be among the first features recalled from participants’ cognitive maps (Osmond, 1963). Cognitive mapping was employed as a participatory method for studying water-based familiarity because it has been used by a number of studies to investigate the extent to which water spatially anchors people’s cognitive maps (Rasmussen, 1931; Southworth, Cranz, Lindsay, & Morhayim, 2012). Certain socioeconomic and age groups were found to have difficulty drawing accurate sketch maps of a large-scale environment, although they were capable of navigating the environment (Clayton & Woodyard, 1981; Downs & Siegel, 1981; Hart, 1981; Lewis, 1976). Instead of acquiring sketch maps, a survey-administered cognitive mapping protocol (instruction two in Table 4.2.) was used as a prompt to obtain the recall sequence of water-based features. These recall sequences served to determine the extent to which these waterscapes were spatial anchors that contributed to water-based familiarity.

1.7.8. Studying water-based place identity with photovoice recall

Although Lynch used photograph recognition to supplement sketch maps and verbal interviews with an egocentric perspective of spatial memory, the photographs were preselected by investigators and may not have been as ecologically or cognitively valid as those obtained from photovoice. Photovoice involves participants taking photographic images to express their impressions of an environment and has been found to be an effective method for place research (Ruggeri, 2014; Wang & Burris, 1997). Thus, photovoice recall protocol was used to investigate a wayfinding aspect of water-based place identity in the sense of identifiability because the most preferred scenes in unfamiliar urban places have been found to be the most identifiable (Herzog, Kaplan, & Kaplan, 1982). Therefore, a photovoice recall protocol was used instead of the actual photovoice protocol during each interview. Participants were guided to recall five pictures, articulate the content of each recalled photograph, and locate the observer's position and viewing angle on a city map because it was not possible for the investigator to travel around the city to take five pictures. In addition, in the absence of the investigator, participants may be inclined to take photographs of salient features to which they have easy access as opposed to making an effort to travel to specific locations to capture the most memorable pictures of an entire city.

2. Methods

2.1. Site selection

Among the alluring water cities that have been considered comparable to Venice (MacLean, 2011; Raplee, 2010), the following six were chosen as study sites based on precipitation pattern similarity and geographical proximity for minimizing sampling cost: Amsterdam and Giethoorn in the Netherlands, Ghent and Bruges in Belgium, and Berlin and Hamburg in Germany. Only Amsterdam and Hamburg are coastal cities with easily accessible harbors, while the other four are inland water cities. Rotterdam, the second largest Dutch city, and Almere, the fastest growing city in Europe, were added to the selection of study sites because similar to Amsterdam and Hamburg, these two coastal polder cities are also appealing water cities with easily accessible harbors (Kwadijk et al., 2010; Tao & Zhengnan, 2013). The final list of study sites comprised four coastal water cities and four inland water cities. This selection of water cities allowed for some level of variability in the amounts and types of water features. All eight water cities have canals, and all four coastal water cities have a water density greater than 10% due to the presence of larger water bodies, such as harbors and lakes. The water density for the inland cities is less than 10%. The water density was calculated by dividing the total surface of water in each city by its total area of land.

2.2. Sampling

A simple and obvious field-interview sampling strategy for residents and visitors in these eight cities does not exist. Each city's nine sampling sites included major entry points, such as airports, inter-city train stations, and bus stations, city halls, tourist bureaus, and various randomly selected hotels, cafes, ethnic stores, and universities.

These sites were chosen to conveniently sample a sufficient mix of residents and visitors, high- and low-income populations, experts of environmental design, non-experts, and immigrants and visitors from varying countries of origin. A randomized order was first used to sequence the eight water cities. A random sequencing of sampling sites was then performed to create an approximation of a random sample that could be as representative of a theoretical sampling frame as possible. This theoretical sampling frame assumed that it is possible to capture all residents and visitors in each water city. Each sampling site was assigned 5 hours of sampling time, which was a total of 45 hours for each water city.

2.3. Data collection and coding

A total of 60 semi-structure interview participants were recruited across all eight water cities' sampling sites to generate measures for aquaphilic urbanism, waterscape attributes, individual factors, city image coherence, and the openness toward water-coherent urbanism. To formulate questions for measuring openness toward water-coherent urbanism, the investigator conducted two open-ended expert interviews with a Landscape Architecture faculty member from a Dutch university and a Dutch consultant with an international non-profit organization specialized in Urban Planning and Design were conducted. Before deployment, four questions were reviewed by six faculty members in Landscape Architecture, Architecture, Urban Planning, and Sociology from an American university.

2.3.1. Measures for water-coherent urbanism

Structured questions were created based on the results of the expert interviews for measuring the public acceptance of water-coherent urbanism as participants' openness to use the public realm for 1) storing public storm water runoff, 2) infiltrating public storm water runoff, 3) water transportation, and 4) canals and creeks. As shown in Appendix L, for the first two questions, a number of possible urban design solutions for storing and infiltrating public runoff were to be rated based on participants' level of support. For the last two questions, participants were asked to rate the likelihood of a series of factors for motivating their willingness to use water transportation or to include more canals or creeks in the urban environment. The ratings were generated based on "very," "somewhat," and "not" as response categories equally spaced along a three-point Likert scale to generate the score of 3, 2, or 1. Each measure was based on the average score of all response ratings.

2.3.2. Aquaphilic urbanism measures

Table 5.1. shows the interview items associated with four variables for measuring aquaphilic urbanism. The cognitive mapping protocol (instruction one) and photovoice exercise (question two) were administered as interview questions to measure water-based familiarity and water-based place identity, respectively. Two structured questions (questions three and four) were used to indicate water-based comfort and water-based place dependence. To assess the respondents' water-based familiarity, instruction one used a cognitive mapping protocol to prompt each participant to recall the city as a map and to identify five features or locations that came to mind first when imagining drawing a map of the city. In addition, to obtain an indicator for water-based place identity, question two engaged each participant in a photovoice exercise to recall five pictures of the city they would use to describe the city to friends who had never been there. The two measures were generated from interview items one and two, first by assigning 1 or 0 as the base score for each answer with or without water. Then, a weight of 5 was applied to the base score for

the first answer given, 4 for the second answer, and so forth to account for the assumed significance of the recall sequence.

Table 5.1.
Aquaphilic urbanism measures.

Variable	Interview items for field participants
Water-based familiarity [a]	1. Cognitive mapping protocol: imagine you are drawing a map of the city. Please name or describe the five features or locations that come to mind first. Please do not consult a city map.
Water-based place identity [a]	1. Photovoice protocol: if you were to take five pictures of the city to describe it to someone who has never been there, what would you take pictures of? What comes to mind first? What comes next?
Water-based comfort [b]	2. How much do the bodies of water in the city help you relax when you are stressed? □ Very much (3) □ Somewhat (2) □ Not at all (1)
Water-based place dependence [b]	3. How much do you use the bodies of water in the city to orient yourself? □ Very much (3) □ Somewhat (2) □ Not at all (1)

a. Code each answer 1 or 0 based on whether or not it references water before assigning a weight from 5 to 1 to account for the sequence of recall. Use a weighted average to create variable measure.
b. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses.

As shown in the following formula, an average was taken from the sum of all five weighted base scores to derive measures for water-based familiarity from the cognitive mapping protocol results and water-based place identity from the photovoice exercise responses:

Weighted average = (5 * first answer base score + 4 * second answer base score + 3 * third answer base score + 2 * fourth answer base score + 1 * fifth answer base score)/5

To measure water-based comfort (item 3 in Table 5.1.), participants were asked to evaluate the extent to which they thought that the water bodies in the city helped them relax when stressed. Similarly, for producing the indicator for water-based place dependence, item 4 in Table 5.1. asked participants to assess the degree to which these water bodies helped them orient themselves. To ordinate the scores for these two items, their response categories were assumed to be equally spaced along a three-point Likert scale.

2.3.3. Waterscape measures

As shown in Table 5.2., to produce the measures of mappability and identifiability for each waterscape type, the results of interview items 1 and 2 were recoded as 1 or 0, depending on whether their answer involved one of the targeted waterscapes, which are canal, harbor, lake, river, and water landmark, as opposed to water in general. The classifications of these waterscapes were based on the literal use of these five waterscape terms or the names of actual water bodies in participants' responses. When a response's waterscape type was unclear, the participant was asked to provide clarification before ending the interview. Mappability and identifiability accounted for the extent to which each of these waterscape types was salient in each participant's (top-down) cognitive map and (eye-level) cognitive image.

A similar coding scheme was applied for interview items 1, 2, and 3 in Table 5.2. to assess the degree to which each participant would likely seek proximity to each waterscape type as a spatial anchor for navigating unknown territories. This arguably generated the measures of canal attachment, harbor attachment, lake attachment, river attachment, and water landmark attachment.

Table 5.2.
Waterscape measures.

Variable	Interview items for field participants
Waterscape mappability	1. Cognitive mapping protocol: imagine you are drawing a map of the city. Please name or describe the five features or locations that come to mind first. Please do not consult a city map.
Waterscape identifiability	2. Photovoice protocol: if you were to take five pictures of the city to describe it to someone who has never been there, what would you take pictures of?
Waterscape attachment	3. Non-visual protocol: what are the five things you would miss about the physical environment if you had to leave the city tomorrow?

a. Code each answer 1 or 0 based on whether or not it contains a targeted waterscape[b]; assign a weight from 5 to 1 to account for the sequence of recall; use weighted averages for measures.
b. A targeted waterscape can be a canal, river, lake, harbor, or a water landmark; a water landmark refers to a landmark along and across water bodies.

2.3.4. Measures for individual factors

Table 5.3. exhibits four interview items for indicating the participants' level of environmental familiarity through their status as a visitors or residents, gender, aquaphilia, and aquaphilia baseline. The response to interview item 1 in Table 5.3. was coded as 1 or 2 for visitors or residents based a length of stay less than or at least 90 days to match the duration for a Schengen visitor visa. A male or female participant was given a score of 1 or 2, respectively, for gender as a categorical variable (item 2 in Table 5.3.). For allocentric aquaphilia, which is the structuralist influence of aquaphilia on acquired

human attachment to water-centric cities, each answer for item 3 in Table 5.3. was assigned a base score of 1 or 0 based on whether or not it referenced water. A weighted average was then generated by multiplying each base score with a weight from 5 to 1. This weighting again accounted for the sequence of recall to reflect the level of emotional salience of each water-based feature. A five-point Likert scale was used to ordinate the score for aquaphilia sensitivity baseline (item 4 in Table 5.3.) based on the assumption of equal spacing between response categories.

Table 5.3.
Measures for individual factors.

Variable	Interview items for field participants
Visitor/Resident [a]	1. How many years/days have you been in this city (altogether)?
Gender [b]	2. Which sex or gender do you identify with? □ Female (2) □ Male (1) □ Other (0)
Allocentric aquaphilia [c]	3. What are the five things you would miss about the physical environment if you had to leave the city tomorrow?
Aquaphilia sensitivity baseline [d]	4. If you could live anywhere, would you choose to live □ right on the water (5) □ with easy access to water (4) □ with visual access to water only (3) □ far away from water (2) □ as far away from water as possible (1)?

a. Code the response with 2 and 1 for residents and visitors using 90 days as a cutoff.
b. Code female and male participants with 2 and 1 to generate a categorical variable.
c. For interview item 3, code each answer 1 or 0 based on whether or not it references water before assigning a weight from 5 to 1 to account for the sequence of recall. Use a weighted average to create variable measure.
d. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses.

2.3.5. City image coherence measures

In between the cognitive mapping and photovoice protocol, participants were guided to sketch their cognitive maps by the following instructions: “Please draw a map of your city on the next page. Include as many features as you can recall. Number the features directly on the map to indicate the sequence in which they emerge in your memory.”

Fifty-five sketch maps were collected from 60 field participants because five participants could not draw their cognitive maps from recall. The sketch maps were presented in a randomized sequence in Qualtrics for evaluation by two independent raters without previous exposure to the study or the eight cities. Raters one and two were instructed to read the pre-survey briefing materials exhibited in Appendix B before selecting a description that best characterized each sketch map from the evaluation rubric also shown in Appendix B. The best-fitting description for each sketch map was coded into a rating using the scoring scheme shown in Appendix L. This scoring scheme that was introduced in Chapter IV was found to generate adequately reliable average ratings between raters one and two. These average ratings were used as the measure of dual-perspective coherence (item 1 in Table 5.4.) in this chapter.

After the first sketch map survey using uncolored sketch maps, the water elements of the 55 sketch maps were colored in blue. These colored sketch maps were presented in a randomized sequence in Qualtrics again for evaluation by two other independent raters (raters three and four) without previous exposure to the study or pre-survey briefing materials. Raters three and four were instructed to scan eight city maps for no longer than 10 seconds to identify the city associated with each colored sketch map for item two in Table 5.4.

Table 5.4.
City image coherence measures.

Variable	Sketch map survey items
Dual-perspective coherence	1. Ratings by raters 1 and 2 using uncolored sketch maps and the evaluation rubric and coding scheme in Appendix M.
Colored allocentric coherence [a]	2. Which city is this map about? □ Almere □ Amsterdam □ Berlin □ Bruges □ Ghent □ Giethoorn □ Hamburg □ Rotterdam □ Not Sure
Contribution of water [b]	3. To what extent do the map's blue features help you identify the city? □ Very much (3) □ Somewhat (2) □ Not (1)
Water-based allocentric coherence	4. The contribution of water to correct map identification. Colored allocentric coherence *(CAC)* * Contribution of water *(CW)*
Water-based egocentric coherence [b]	5. To what extent do non-blue features cluster along blue features? □ Very much (3) □ Somewhat (2) □ Not (1)

a. Code 1 or 0 for indicating correct or incorrect city identification.
b. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses.

To generate the measure of colored map allocentric coherence, which is the identifiability of colored sketch maps, a base score of 1 or 0 was assigned to indicate correct or incorrect map identification. This base score was then multiplied by the contribution of water as a weight to generate the measure of water-based allocentric coherence (item 4 in Table 5.4.). Contribution of water (item 3 in Table 5.4.) was based on the degree to which water helped the raters identify the city associated with each sketch map. Lastly, raters three and four were asked to assess the extent to which non-blue features clustered along the blue features on each sketch map to produce the indicator of water-based egocentric coherence (item 5 in Table 5.4.). This interview question measured the degree to which water helps the sequencing of identifiable scenes into procedural knowledge. A three-point Likert scale was used to ordinate the responses for contribution of water and water-based egocentric coherence. The measures for items 2-5 in Table 5.4. were derived from the average ratings between raters three and four, which have been found to have sufficient inter-rater reliability, as shown in Chapter IV.

2.4. Data analysis

2.4.1. Data reduction

In Appendices M and N, the correlation tables for the measures of aquaphilic urbanism and water-coherent urbanism showed that a number of these measures were correlated. As a result, an internal consistency reliability test (based on Cronbach's alpha) and a principal component analysis (PCA) using the-eigenvalue-greater-than-one rule were conducted to reduce these measures to a smaller set of uncorrelated variables as components (Kaiser, 1960; McGraw & Wong, 1996). The PCA was also used to provide content validity for the measures of water-based imageability and water-based goal affordance by verifying whether these measures were reducible into their respective component constructs. Components are linear combinations of variables based on weights (eigenvectors) developed by an analysis (Jolliffe, 2002). Principal components represent most of the information in the original set of variables. The first principal component extracted captures as much of the variability in the data as possible. Each succeeding component accounts for as much of the remaining variability as possible. A correlation matrix was used to perform the PCA because the units of measurement of the individual measures differed.

2.4.2. Mediation analysis

Franck (2001) pointed out the importance of studying the indirect effects of environment on behaviors to address the criticism of environmental determinism as a dominant perspective or assumption in environment-behavior studies. To identify how the design interventions mediated seemingly environmentally determined behaviors as a basis for deriving evidence-based design guidelines, mediation analyses in SPSS Statistics 22 using a macro written by Preacher and Hayes (2008) were conducted. A mediation model is typically used to identify the underlying mechanism of an observed relationship between an independent variable and a dependent variable by including one or more mediators as explanatory variables (MacKinnon, Fairchild, & Fritz, 2007; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002).

2.4.3. Macro-level mediation analyses

Macro-level mediation analyses were used to investigate the extent to which each of the three components, aquaphilic urbanism, water-based goal affordance, and water-based imageability, mediated the effect of water densities/watershed locations (independent variable) on the amount of allocentric aquaphilia as measured by item 3 in Table 5.3. This study also examined the effect of each of these three components (as an independent variable) on the openness toward water-coherent urbanism (as the dependent variable) with allocentric aquaphilia as a potential mediator.

2.4.4. Micro-level mediation analyses

Micro-level mediation analyses were conducted to understand how waterscape attributes mediated the effects of gender and familiarity on individually perceived water-based imageability while controlling aquaphilia sensitivity baseline as a covariate. Gender and the group variable of visitors or residents rotated as the independent variable. Dual-perspective coherence, water-based allocentric coherence, and water-based egocentric coherence alternated as the dependent variable. A mediation analysis for each combination of independent and dependent variable with each waterscape attribute indicator as a mediator was conducted. Multiple mediation analyses were also conducted when more than one waterscape attribute indicator significantly mediated the relationship between the same independent and dependent variables. Only those analyses with significant outcomes are reported in Appendix P and summarized in section 3.

3. Results

3.1. Data reduction based on internal consistency reliability and PCA results

3.1.1. Water-based goal affordance and water-based imageability

Appendix M shows the results of the internal consistency reliability tests and the PCA conducted for the four measures of aquaphilic urbanism. Based on .6 as the threshold for Cronbach's alpha (Hume, Ball, & Salmon, 2006), these four measures could be condensed into fewer variables because they had an acceptable internal consistency reliability ($\alpha = .71 > .6$). With promax rotation and the-eigenvalue-greater-than-one rule (Kaiser, 1960), the PCA extracted two principal components to explain approximately 2.44 and 1.08 of the variable worth, or 60.88% and 27.01% of the four measures' total variance, respectively. As illustrated in Appendix M, the loadings (simple correlations) between each of the four measures and either of these two components were either close to zero or much higher than the correlations between the same measures. In addition, the residual correlations, or the differences between observed and reproduced correlations, were less than .3, indicating an absence of uncaptured strong correlations between residuals. Most residual correlations' absolute values were less than .05, while the residual correlation between water-based place identity and water-based familiarity was less than .3. These relatively small residuals showed that the variances in the measures were well-captured by the component scores. The PCA outcome in Appendix M suggests water-based goal affordance, as the first principal component, parsimoniously represents water-based place dependence and water-based comfort, while water-based imageability, as the second principal component, effectively denotes water-based familiarity and water-based place identity. A composite score for aquaphilia urbanism, which was the dependent variable, was then produced by SPSS using the two component scores in the covariance matrix to weight these two principal components as the independent variables of a linear regression.

3.1.2. People's openness toward water-coherent urbanism

Appendix N illustrates the internal consistency reliability test and the PCA results for the four measures of participants' openness toward water-coherent urbanism. These four measures underwent data reduction because they had an adequate internal consistency reliability (α=.86>.6). With 1 as the eigenvalue threshold, the PCA extracted one component, which accounted for 3.02 of the variable worth and 60.31% of the total variance in the four measures. The loadings or simple correlations between each of the four measures and the component were greater than .3, and their residential correlations were less than .3. These findings indicate that the principle component score for participants' openness toward water-based coherent urbanism effectively represents all four measures. The score was calculated from summing the weighted measures generated by multiplying each of the four measures with its corresponding coefficients as weights.

3.2. Macro-level mediation analysis results

Appendix O illustrates the results of the macro-level mediation analyses, which are summarized in the following sections.

3.2.1. Aquaphilic urbanism as a mediator of the effect of water density on allocentric aquaphilia

Model A in Table 5.5. shows that aquaphilia seemed to be environmentally determined by high versus low water (density) city, that is, each city's coastal/downstream or inland/upstream location. However, this significant indirect effect, or ostensible phenomenon of environmental determinism, was fully mediated by aquaphilic urbanism as a water-based sense of place that evokes aquaphilia. Such a sense of place encompasses water-based familiarity, water-based comfort, water-based place dependence, and water-based place identity, to create a water-based sense of place that evokes aquaphilia (β_a= 1.46, p_a<.001; β_b= .33, p_b<.001; β_c= .64, p_c<.01; $\beta_{c'}$= .15, $p_{c'}$>.05; R^2=.34, F (2, 57) =14.96, p<.001). The results suggest that a higher level of water density does not always lead to a higher level of allocentric aquaphilia because of the potential of aquaphilic urbanism to be a mediator of this relation. In other words, inland and upstream cities (with a lower water density than downstream cities along the coasts) can evoke a greater level of allocentric aquaphilia by increasing their water densities.

Table 5.5.
Mediation analysis results for aspects of aquaphilic urbanism as mediators on the relationship between watershed locations and allocentric aquaphilia.

Model	A	t_a	B	t_b	C	t_c	C'	$t_{c'}$	R^2	F
A^a	1.46***	4.15	.33***	4.45	.64**	2.76	.15	.65	.34	14.96***
A_1^b	.51*	2.05	.41***	3.77	.64**	2.75	.43	1.96	.29	11.75***
A_2^c	1.23***	5.99	.41**	2.86	.64**	2.76	.15	.53	.23	8.37***
A_{31}^d	.52*	2.06	.35**	3.19	.64**	2.76	.10	.39	.35	9.89***
A_{32}^d	1.23***	5.99	.29*	2.16						

Note: ****p*<.001; ** *p*<.01; * *p*<.05; independent variable: high or low water city; dependent variable: allocentric aquaphilia.

a. Mediator: aquaphilic urbanism.
b. Mediator: water-based goal affordance.
c. Mediator: water-based imageability.
d. Mediator 1: water-based goal affordance; mediator 2: water-based imageability.

3.2.2. Functional or aesthetic aspects of aquaphilic urbanism as adaptation motivators

Model A_1 in Table 5.5. reveals that water-based goal affordance fully mediated 29% of the contribution of the group variable of high or low water city to allocentric aquaphilia (β_a= .51, p_a<.05; β_b=.41, p_b<.001; β_c= .64, p_c<.01; $\beta_{c'}$= .15, $p_{c'}$>.05; R^2=.29, F(2, 57)=11.75, *p*<.001). In model A_2, 23% of the influence of the group variable of high or low water city on allocentric aquaphilia was fully mediated by water-based imageability (β_a= 1.23, p_a<.001; β_b= .41, p_b<.01; β_c= .64, p_c<.01; $\beta_{c'}$= .15, $p_{c'}$>.05; R^2=.23, F(2, 57)=8.37, *p*<.001). Compared to water-based imageability, the mediating effect of water-based goal affordance was 6% higher. When both mediators were included in model A_3, they accounted for a total of 35% of the high and low water city's influence on allocentric aquaphilia (β_{a1}= .52, p_{a1}<.05; β_{b1}= .35, p_{b1}<.01; β_{a2}= 1.23, p_{a2}<.001; β_{b2}= .29, p_{b2}<.05; β_c= .1, p_c>.05; $\beta_{c'}$= .10, $p_{c'}$>.05; R^2=.35, F(2, 57)=9.89, *p*<.001). The combined effect of both mediators was only 6% higher than the mediating effect of water-based goal affordance alone. A comparison of all four models suggests the potential of either functional or aesthetic aspects of aquaphilic urbanism alone to increase allocentric aquaphilia.

3.2.3. Aquaphilia as the function of aquaphilic urbanism for adaptation

In Table 5.6., model B (R^2=.10, F(2, 57)=3.16, p<.05) indicates that a water city's watershed location did not influence public acceptance of water-coherent urbanism because the group variable of high or low water city had no significant indirect or direct effect on people's openness toward water-coherent urbanism (β_c= .31, p_c>.05; $\beta_{c'}$= .05, $p_{c'}$>.05); however, model B's a path indicates that high water cities in downstream locations along the coast were more likely to embody aquaphilic urbanism than low water cities further inland in upstream locations (β_a= 1.46, p_a<.001), and its b path shows that aquaphilic urbanism had a significant positive effect on openness toward water-coherent urbanism (β_b= .18, p_b<.05).

Model C shows that the significant influence of aquaphilic urbanism on openness toward water-coherent urbanism was an indirect effect fully mediated by allocentric aquaphilia (β_a= .36, p_a<.001; β_b= .31, p_b<.05; β_c= .19, p_c<.01; $\beta_{c'}$= .08, $p_{c'}$>.05; R^2=.17, F(2, 57)=5.76, p<.01). This result indicates that aquaphilic urbanism helps introduce water-coherent urbanism as one of the mainstream urban design approaches by tending to produce allocentric aquaphilia. The findings of models A, B, and C suggest that water-coherent urbanism could be applied more to instigate public acceptance through allocentric aquaphilia as the product of aquaphilic urbanism.

Table 5.6.
Mediation analysis results for exploring relationships among watershed locations, allocentric aquaphilia, aquaphilic urbanism, and openness toward water-coherent urbanism.

Model	A	t_a	B	t_b	C	t_c	C’	$t_{c'}$	R^2	F
A[b]	1.46***	4.15	.33***	4.45	.64**	2.76	.15	.65	.34	14.96***
B[c]	1.46***	4.16	.18*	2.11	.31	1.34	.05	.20	.10	3.16*
C[d]	.36***	5.46	.31*	2.17	.19**	2.53	.08	.85	.17	5.76**

a. ****p*<.001; ** *p*<.01; * *p*<.05.
b. Independent variable (IV): high or low water city; mediator: aquaphilic urbanism; dependent variable (DV): allocentric aquaphilia.
c. IV: high or low water city; mediator: aquaphilic urbanism; DV: openness toward water-coherent urbanism.
d. IV: aquaphilic urbanism; mediator: allocentric aquaphilia; DV: openness toward water-coherent urbanism.

3.2.4. Aquaphilia as the function of water-based imageability toward human adaptation

Table 5.7. compares model C with models C_1 and C_2. Model C indicates that allocentric aquaphilia fully mediated 17% of the indirect effect of aquaphilic urbanism on participants’ openness toward water-coherent urbanism.

Table 5.7.
Mediation analysis results for the mediating effect of allocentric aquaphilia on the relationship between aspects of aquaphilic urbanism and openness toward water-coherent urbanism.

Model	A	t_a	B	t_b	C	t_c	C’	$t_{c'}$	R^2	F
C[b]	.36***	5.46	.31*	2.17	.19**	2.53	.08	.85	.17	5.76**
C_1[c]	.47***	4.33	.38**	2.82	.18	1.55	.00	.04	.16	5.33**
C_2[d]	.45***	4.08	.28*	2.16	.33**	2.96	.20	1.67	.20	6.98**

a. ****p*<.001; ** *p*<.01; * *p*<.05; mediator: allocentric aquaphilia; dependent variable: openness toward water-coherent urbanism.
b. Independent variable (IV): aquaphilic urbanism.
c. IV: water-based goal affordance.
d. IV: water-based imageability.

Model C_1 shows that allocentric aquaphilia had no mediating effect when water-based goal affordance replaced aquaphilic urbanism as the independent variable (β_a= .47, p_a<.001; β_b= .39, p_b<.01; β_c= .17, p_c>.05; $\beta_{c'}$= -.01, $p_{c'}$>.05; R^2=.16, F(2, 57)=5.44, p<.01). In contrast, allocentric aquaphilia mediated 20% of the effect of water-based imageability on participants' openness to water-coherent urbanism in model C_2 (β_a= .45, p_a<.001; β_b= .28, p_b<.05; β_c= .31, p_c<.01; $\beta_{c'}$= .20, $p_{c'}$>.05; R^2=.20, F (2, 57) =6.97, p<.01) as opposed to 17% in model C with aquaphilic urbanism as the independent variable. In summary, functionally-derived allocentric aquaphilia did not fully mediate the indirect impact of water-based goal affordance on the participants' acceptance of water-coherent urbanism. In contrast, aesthetically-derived allocentric aquaphilia evidently fully mediated the indirect effect of water-based imageability on participants' openness toward water-coherent urbanism. The findings reveal that water-based imageability underpins the influence of allocentric aquaphilia. This influence is essential for motivating cities and individuals to support a more widespread application of water-coherent urbanism.

3.3. Intervening influences for gender effect on coherence measures

Canal mappability, canal identifiability, or both variables were included as intervening variables for three different micro-level models using aquaphilia sensitivity baseline as a covariate, gender as the independent variable, and each coherence measure as the dependent variable. All model results can be found in Appendix P, but the following sections only report results from the best-fitting model with the highest adjusted R square for each coherence measure.

3.3.1. No gender effect on dual-perspective coherence

Using dual-perspective coherence as the dependent variable, model D (Adj-R^2 = .20, F (4, 46) = 4.11) in Table 5.8. shows that the best-fitting model contained both intervening variables; however, while canal mappability significantly influenced dual-perspective coherence (β_{b1}= .35, p_{b1}<.01), canal identifiability did not (β_{b2}= -.26, p_{b2}>.05). The significant gender effect on canal identifiability (β_{a2}= -1.37, p_{a2}<.05) did not induce a significant gender effect on dual-perspective coherence (β_c= -.42, p_c>.05; $\beta_{c'}$=-.23, $p_{c'}$>.05).

Table 5.8.
Intervening influences for gender effect on coherence measures.

Model	A	t_a	B	t_b	C	t_c	C’	$t_{c'}$	Adj-R^2	F
D_1[a]	-1.57	-1.83	.35**	2.93	-.42	-.66	-.23	-.36	.20	4.11**
D_2[a]	-1.37*	-2.15	-.26	-1.59						
E[b]	-1.74*	-2.20	.21***	5.21	-.62*	-2.16	-.25	-1.02	.47	16.98***
F[c]	-1.57 ⁻	-1.83	.12**	3.43	-.36	-.84	-.29	-2.20	.31	6.96***

Note: ****p*<.001; ** *p*<.01; * *p*<.05 ⁻ *p*<.10; independent variable: gender (1: male; 2: female); control variable (d): aquaphilia sensitivity baseline.

a. Dependent variable (DV): dual-perspective coherence; mediator 1: canal mappability; mediator 2: canal identifiability; β_d= -.96*; t_d=-2.53
b. DV: water-based allocentric coherence; Mediator: canal mappability; β= -.55***; t=-3.76.
c. DV: water-based egocentric coherence; Mediator: canal mappability; β= -.28*; t= -2.20.

3.3.2. Mediation of gender effect on water-based allocentric coherence by canal mappability

When water-based allocentric coherence was the dependent variable, the best-fitting model (model E in Table 5.8.) only had canal mappability as an intervening variable. Model E (Adj-R^2 = .47, F (3, 52) = 16.98, *p*<.001) shows that canal mappability fully mediated the significant gender effect on water-based allocentric coherence (β_a= -1.74, p_a<.05; β_b= .21, p_b<.001; β_c= -.62, p_c<.05; $\beta_{c'}$= -.25, $p_{c'}$>.05).

3.3.3. No gender effect on water-based egocentric coherence

Among the models using water-based egocentric coherence as the dependent variable, the best-fitting model (model F) contained only canal mappability as an intervening variable. Model F (Adj-R^2=.31, F(3, 47)=6.96, p<.001) indicates that there was a marginally significant gender effect on canal mappability (β_a=-1.57, p_a<.10), which then significantly influenced water-based egocentric coherence (β_b= .12, p_b<.01); however, gender had no significant effect on water-based egocentriccoherence (β_c= -.36, p_c>.05; $\beta_{c'}$=-.17, $p_{c'}$>.05).

3.4. Intervening influences for effect of visitors or residents on coherence measures

Similarly, using canal mappability, canal identifiability, or both as intervening variables, three models were tested for the group variable of visitors or residents as the independent variable with aquaphilia sensitivity baseline as a covariate and each coherence measure as the dependent variable. All model outputs can be found in Appendix P. For each coherence measure, the results from the best-fitting model with the highest adjusted R square are summarized in the following sections.

3.4.1. Mediation of group effect on dual-perspective coherence by canal mappability

With dual-perspective coherence as the dependent variable, the best-fitting model (model G in Table 5.9.) included both canal mappability and identifiability as intervening variables. Unlike model D, which shows no significant gender effect on dual-perspective coherence, model G (Adj-R^2 =.22, F (3, 47) = 4.50, p<.01) indicates that dual-perspective coherence significantly differed between visitors and residents (β_c= 1.13, p_c<.05). While canal identifiability had no significant mediating effect (β_{a2}=-.39, p_{a2}>.05; β_{b2}= -.19, p_{b2}>.05), canal mappability fully mediated the significant group effect of visitor versus resident on dual-perspective coherence with a marginal significance (β_{a1}=1.35, p_{a1}<.10; β_{b1}= .30, p_{b1}<.05; $\beta_{c'}$=.64, $p_{c'}$>.05; β_d= -.96, p_d<.05).

Table 5.9.
Intervening influences for the effect of visitors or residents on coherence measures.

Model	A	t_A	B	t_B	C	t_C	C'	$t_{C'}$	Adj-R^2	F
G_1[a]	1.35⁻	1.74	.30*	2.41	1.13*	2.04	.64	1.12	.22	4.50**
G_2[a]	-.39	-.66	-.19	-1.17						
H[b]	1.32	1.82	.24***	5.92	.03	.12	-.28	-1.29	.47	17.37***
I[c]	1.35	1.75	.14***	4.34	-.20	-.97	-.40*	-2.16	.32	8.85***

Note. ****p*<.001; ** *p*<.01; * *p*<.05; ⁻ *p*<.10; independent variable: visitors or residents (1: visitor; 2: resident); control variable (d): aquaphilia sensitivity baseline.

a. Dependent variable (DV): dual-perspective coherence; mediator 1: canal mappability; mediator 2: canal identifiability; β_d=-.96*; t_d=-2.65.
b. DV: water-based allocentric coherence; mediator: canal mappability; β= -.35**; t=-2.88.
c. DV: water-based egocentric coherence; mediator: canal mappability; β_d= -.60***; t_d= -4.27.

3.4.2. No significant effect of visitors or residents on water-based allocentric coherence

The best-fitting model (model H in Table 5.9.) for water-based allocentric coherence as the dependent variable only had canal mappability as the intervening variable. Model H indicates that canal mappability was significantly associated with water-based allocentric coherence (β_b= .24, p_b<.001). In model H, no group effect of visitors or residents was found for canal mappability (β_a= 1.32, p_a>.05) or water-based allocentric coherence (β_c= -.03, p_c>.05; $\beta_{c'}$=-.30, $p_{c'}$>.05).

3.4.3. Significantly higher water-based egocentric coherence for visitors

With water-based egocentric coherence as the dependent variable, the best-fitting model (model I in Table 5.9.) (R^2=.36, F (3, 47) =11.69, *p* <.001) shows no significant group effect of visitors or residents on canal mappability (β_a= 1.35, p_a>.05) while canal mappability had a significant positive relationship with water-based egocentric coherence (β_b= .14, p_b<.001). Model I indicates that the intervening effect of canal mappability made the group effect of visitors or residents on water-based egocentric coherence significant ($\beta_{c'}$= -.20, $p_{c'}$>.05; $\beta_{c'}$= -.40, $p_{c'}$<.05).

3.5. Mediation of the canal identifiability effect on coherence by canal mappability

For mediation models J, K, and L in Table 5.10., canal identifiability was used as the independent variable, canal mappability was used as the mediator, and each of the following coherence measures were used as the dependent variable: dual-perspective coherence, water-based allocentric coherence, and water-based egocentric coherence.

Table 5.10.

Mediation of the canal identifiability effect on coherence by canal mappability.

Model	A	t_A	B	t_B	C	t_C	C'	$t_{C'}$	Adj-R^2	F
J_1[a]	.72***	4.33	.35**	2.93	-.00*	-.03	-.26	-1.59	.20	4.11**
J_2[b]	.80***	5.32	.30*	2.41	.05	.37	-.19	-1.17	.22	4.50**
K_1[c]	.66***	4.08	.18***	3.96	.19**	3.20	.08	1.20	.47	13.20***
K_2[d]	.79***	5.25	.21***	4.23	.23***	3.68	.06	.93	.47	13.21***
L_1	.72***	4.33	.12**	2.82	.09⁻	1.77	.01	.10	.25	5.11**
L_2	.80***	5.32	.15***	3.63	.10*	2.08	-.02	-.38	.31	6.55***

Note: ***p<.001; ** p<.01; * p<.05; ⁻ p<.10; independent variable: canal identifiability; mediator: canal mappability; covariate 1 (d_1): aquaphilia sensitivity baseline.

a. Dependent variable (DV): dual-perspective coherence; covariate 2 (d_2): gender (1: male; 2: female); β_{d1}= -.96*; t_{d1}= -2.53; β_{d2} = -.23; t_{d2} = -.36.
b. DV: dual-perspective coherence; covariate 2 (d_2): visitors or residents (1: visitor; 2: resident); β_{d1}= -.96**; t_{d1}=-2.65; β_{d1}=.64; t_{d1}=1.12.
c. DV: water-based allocentric coherence; covariate 2 (d_2): gender (1: male; 2: female); β_{d1}= -.55***; t_{d1}=-3.77; β_{d1}= -.22; t_{d1}=-.89.
d. DV: water-based allocentric coherence; covariate 2 (d_2): visitors or residents (1: visitor; 2: resident); β_{d1}= -.59*; t_{d1}= -4.20; β_{d1}= -.21; t_{d1}= -.89.
e. DV: water-based egocentric coherence; covariate 2 (d_2): gender (1: male; 2: female); β_{d1}= -.29*; t_{d1}=-2.18; β_{d1}= -.17; t_{d1}=-.80.
f. DV: water-based egocentric coherence; covariate 2 (d_2): visitors or residents (1: visitor; 2: resident); β_{d1}= -.35**; t_{d1}=-2.86; β_{d1}=-.45*; t_{d1}=-2.16.

In addition to aquaphilia sensitivity baseline as a covariate, each model alternately included either gender (for subscript model 1) or the group variable of visitors or residents (for subscript model 2) as another covariate.

3.5.1. Dual-perspective coherence as a dependent variable

Model J_1 (Table 5.10.) shows that canal mappability fully mediated the effect of canal identifiability on dual-perspective coherence in the presence of gender as a second covariate in addition to aquaphilia sensitivity baseline ($\beta_a = .73$, $p_a < .001$; $\beta_b = .35$, $p_b < .01$; $\beta_c = -.00$, $p_c < .05$; $\beta_{c'} = -.26$, $p_{c'} > .05$; $\beta_{d1} = -.96$, $p_{d1} < .05$; $\beta_{d2} = -.23$, $p_{d2} > .05$; Adj-$R^2 = .20$, $F\,(4, 46) = 4.11$, $p < .01$).

In contrast, no mediation effect was observed ($\beta_c = .05$, $p_c > .05$; $\beta_{c'} = -.19$, $p_{c'} > .05$; $\beta_{d1} = -.96$, $p_{d1} < .01$; $\beta_{d2} = .64$, $p_{d2} > .05$; Adj-$R^2 = .22$, $F\,(4, 46) = 4.50$, $p < .01$) when the group variable of visitors or residents replaced gender as a covariate in model J_2; however, the positive correlations between canal identifiability and canal mappability and between canal mappability and dual-perspective coherence remained significant ($\beta_a = .80$, $p_a < .001$; $\beta_b = .30$, $p_b < .05$) in model J_2.

3.5.2. Water-based allocentric coherence as a dependent variable

Canal mappability fully mediated the effect of canal identifiability on water-based allocentric coherence for both models K_1 ($\beta_a = .66$, $p_a < .001$; $\beta_b = .18$, $p_b < .001$; $\beta_c = .19$, $p_c < .01$; $\beta_{c'} = .08$, $p_{c'} > .05$; $\beta_{d1} = -.55$, $p_{d1} < .001$; $\beta_{d2} = -.22$, $p_{d2} > .05$; Adj-$R^2 = .47$, $F\,(4, 46) = 13.20$, $p < .001$) and K_2 ($\beta_a = .79$, $p_a < .001$; $\beta_b = .21$, $p_b < .001$; $\beta_c = .23$, $p_c < .001$; $\beta_{c'} = .06$, $p_{c'} > .05$; $\beta_{d1} = -.59$, $p_{d1} < .05$; $\beta_{d2} = -.21$, $p_{d2} > .05$; Adj-$R^2 = .47$, $F\,(4, 46) = 13.21$, $p < .001$). Gender was a significant covariate in model K_1, while the group variable of visitors or residents was not a significant covariate in Model K_2.

3.5.3. Water-based egocentric coherence as a dependent variable

In model L_1 (Table 5.9.), canal mappability fully mediated the marginally significant effect of canal identifiability on water-based egocentric coherence when gender was included as an insignificant covariate (β_a= .72, p_a<.001; β_b= .12, p_b<.01; β_c= .09, p_c<.10; $\beta_{c'}$= .01, $p_{c'}$>.05; β_{d1} = -.29, p_{d1}<.05; β_{d2} = -.17, p_{d2}>.05; Adj-R^2=.25, F (4, 46) = 5.11, p<.01). Model L_2 (Table 5.9.) shows a full mediation of the canal identifiability effect's influence on water-based egocentric coherence by canal mappability with the group variable of visitors or residents as a significant covariate (β_a= .80, p_a<.001; β_b= .15, p_b<.001; β_c=.10, p_c<.05; $\beta_{c'}$= -.02, $p_{c'}$>.05; β_{d1} = -.35, p_{d1}<.01; β_{d2} = -.45, p_{d2}<.05; Adj-R^2=.31, F (4, 46) = 6.55, p<.001).

3.6. Mediation of the water-based allocentric coherence effect on canal attachment by canal identifiability

Using canal mappability, canal identifiability, or both variables as mediators, three mediation models were analyzed to explore the significant relationship between water-based allocentric coherence and canal attachment with gender, visitors or residents, and aquaphilia sensitivity baseline as covariates. Model M in Table 5.11. reports the model with canal identifiability as the mediator (model M) and the highest adjusted R square (β_a= .83, p_a<.01; β_b= .61, p_b<.001; β_c=.62, p_c<.05; $\beta_{c'}$=.11, $p_{c'}$<.05; β_{d1} =-.11, p_{d1}>.05; β_{d2} =-.29, p_{d2}>.05; β_{d3} =-.04, p_{d3}>.05; Adj-R^2=.32, F (5, 50) =11.69, p<.001). Appendix P shows a full mediation for all three models.

Table 5.11.
Mediation analysis results for canal identifiability as a mediator for the effects of water-based allocentric coherence and canal mappability on canal attachment.

Model	a	t_A	b	t_B	c	t_C	c'	$t_{C'}$	Adj-R^2	F
M^a	.83**	3.20	.61***	4.40	.62*	2.06	.11	.40	.32	6.09***
$M_{11}{}^b$	1.64***	5.43	.09	.70	.62*	2.06	-.00	-.00	.31***	5.11***
$M_{12}{}^b$	.83**	3.20	.56***	3.66						
N^c	.42***	4.79	.56***	3.71	.33**	3.11	.09	.82	.32	6.25***

Note: ****p*<.001; ** *p*<.01; * *p*<.05; $^-$ *p*<.10; dependent variable: canal attachment; control variable 1 (d_1): aquaphilia sensitivity baseline; control variable 2 (d_2): gender; control variable 3 (d_3): visitors or residents.

a. Independent variable (IV): water-based allocentric coherence; mediator: canal identifiability; β_{d1}= -.11; t_{d1}= -.31; β_{d2}= -.29; t_{d2}= -.50; β_{d3}= -.04; t_{d3}= -.08.
b. IV: water-based allocentric coherence; mediator 1: canal mappability; mediator 2: canal identifiability; β_{d1}= -.19; t_{d1}= -.50; β_{d2}= -.27; t_{d2}= -.47; β_{d3}= -.18; t_{d3}= -.74.
c. IV: canal mappability; mediator: canal identifiability; β_{d1}= -.19; t_{d1}= -.50; β_{d2}= -.27; t_{d2}= -.47; β_{d3}= -.18; t_{d3}= -.34.

3.6.1. Canal identifiability mediated effect of canal mappability on canal attachment

Model M in Table 5.11. had a higher adjusted R square than Model M_1 using both canal identifiability and canal mappability as mediators. This result suggests that canal identifiability may potentially mediate the effect of canal mappability on canal attachment. Model N in Table 5.11. confirms that canal identifiability fully mediated the significant path between canal mappability and canal attachment (β_a= .42, p_a<.001; β_b= .56, p_b<.001; β_c=.33, p_c<.01; $\beta_{c'}$=.09, $p_{c'}$>.05; β_{d1} =-.19, p_{d1}>.05; β_{d2} =-.27, p_{d2}>.05; β_{d3} =-.18, p_{d3}>.05; Adj-R^2=.32, F (5, 50) =6.25, *p*<.001).

3.7. Mediators for the effect of water-based egocentric coherence on canal attachment

3.7.1. Canal mappability mediated the effect of water-based egocentric coherence on canal attachment

Models O, O_1, and O_2 in Table 5.12. show three mediation analyses conducted for the effect of water-based egocentric coherence on canal attachment using canal mappability, canal identifiability, and both canal mappability and identifiability as mediators.

Table 5.12.
Mediation analysis results for the mediating effects of canal mappability and identifiability on the relationship between water-based egocentric coherence and canal attachment.

Model	a	t_A	b	t_B	c	t_C	c’	$t_{C'}$	Adj-R^2	F
O^a	1.89***	3.98	.28*	2.31	1.04*	2.52	.51	1.11	.21	3.64**
$O_1{}^b$	.65	1.63	.54***	4.13	1.04**	2.52	.69⁻	1.89	.36	6.58***
$O_{21}{}^c$	1.89***	3.98	.04	.32	1.04*	2.52	.63	1.50	.35	5.39***
$O_{22}{}^c$	.66	1.63	.51**	3.22						

Note: ***p<.001; ** p<.01; * p<.05; ⁻ p<.10; IV: water-based egocentric coherence; DV: canal attachment; control variable 1 (d_1): aquaphilia sensitivity baseline; control variable 2 (d_2): gender; control variable 3 (d_3): visitors or residents.

a. Mediator: canal mappability; β_{d1}= -.06; t_{d1}= -.14; β_{d2}= -.86; t_{d2}= -1.34; β_{d3}= -.38; t_{d3}= -.63.
b. Mediator: canal identifiability; β_{d1}= .07; t_{d1}= .18; β_{d2}= -.43; t_{d2}= -.72; β_{d3}=.30; t_{d3}=.58.
c. Mediator 1: canal mappability; mediator 2: canal identifiability; β_{d1}= .04; t_{d1}= .10; β_{d2}= -.43; t_{d2}= -.72; β_{d3}=.21; t_{d3}= .37.

Model O indicates that canal mappability fully mediated 21% of the relationship between water-based egocentric coherence and canal attachment (β_a=1.89, p_a<.001; β_b= .28, p_b<.05; β_c=1.04, p_c<.05; $\beta_{c'}$=.51, $p_{c'}$>.05; β_{d1} =-.06, p_{d1}>.05; β_{d2} =-.86, p_{d2}>.05; β_{d3} =-.38, p_{d3}>.05; Adj-R^2=.21, F (5, 50) =3.64, p<.01). In contrast, canal identifiability did not fully mediate the relationship between water-based egocentric coherence and canal attachment, although model O_1 had the highest adjusted R square compared to Models O and O_2 (β_a=.65, p_a>.05; β_b= .54, p_b<.001; β_c=1.04, p_c<.01; $\beta_{c'}$=.69, $p_{c'}$<.10; β_{d1} =.04, p_{d1}>.05; β_{d2} =-.43, p_{d2}>.05; β_{d3} =.21, p_{d3}>.05; Adj-R^2=.36, F (5, 50) =6.58, p<.001).

3.7.2. Canal mappability and identifiability combined fully mediated the effect of water-based egocentric coherence on canal attachment

Model O_2 shows that an additional 14% of the influence of water-based egocentric coherence on canal attachment could be explained by canal identifiability on top of the 21% by canal mappability in Model O (β_{a1}= 1.89, p_{a1}<.001;β_{b2}= .51, p_{b2}<.01; β_c=1.04,

p_c<.05; $\beta_{c'}$=.63, $p_{c'}$>.05; β_{d1}=-.04, p_{d1}>.05; β_{d2}=-.43, p_{d2}>.05; β_{d3}=.21, p_{d3}>.05; Adj-R^2=.35, F (6, 49) =5.39, p<.001); however, the relationships between water-based egocentric coherence and canal identifiability (β_{b1}= .04, p_{b1}>.05) and between canal mappability and canal attachment became insignificant (β_{a2}=.66, p_{a2}>.05) due to a full mediation of the relationship between canal mappability and canal attachment by canal identifiability, as previously illustrated by model N.

4. Discussions

4.1. Constructs of aquaphilic urbanism as a water-based sense of place

Aquaphilic urbanism, or a water-based sense of place, is composed of water-based imageability and water-based goal affordance as its interrelated aesthetic and functional sub-aspects. Water-based imageability can be measured by waterscape salience in two-dimensional cognitive maps (water-based familiarity), and waterscape identifiability can be measured by eye-level cognitive images (water-based place identity). Water-based goal affordance can be operationalized by the extent to which water helps mitigate stress responses (water-based comfort) and facilitates self-orientation (water-based place dependence) (section 3.1.1.).

4.2. Aquaphilic urbanism for inland and upstream cities with a low water density

Compared with inland and upstream cities, coastal and downstream water cities tend to be associated with a greater presence of water bodies and are thus more likely to embody aquaphilic urbanism; however, aquaphilic urbanism, as an urban design intervention for retrofitting inland and upstream cities, can help defy this ostensible phenomenon of environmental determinism (section 3.2.1.). Inland and upstream cities with a low water density can potentially enhance their appeal to individuals and businesses by increasing its water-based place attachment through implementing aquaphilic urbanism.

4.3. Water-based goal affordance for facilitating environmental adaptation

While water-based goal affordance does not encourage more application of water-coherent urbanism through allocentric aquaphilia (section 3.2.4.), it mediates the indirect effect of watershed locations, or water density, on allocentric aquaphilia more effectively than water-based imageability (section 3.2.2.). This result suggests that for drought-challenged inland and upstream cities with little space in the public realm for large-scale water retention, urban design can still evoke allocentric aquaphilia through the use of smaller-scale waterscapes. These waterscapes can facilitate stress reduction and ease self-orientation in the public realm to increase water-based goal affordance (section 3.2.2). These attractive local waterscapes may help contribute to the environmental adaptation of newcomers through the structuralist influence of aquaphilia on topophilia. Future research should investigate how to design these waterscapes to better help with stress reduction and navigation with less consumption of land and water by quantifying water surface areas.

4.4. Water-based imageability for facilitating water-coherent urbanism through allocentric aquaphilia

The potential of allocentric aquaphilia to motivate public acceptance of water-coherent urbanism (section 3.2.3.) depends mainly upon the aesthetic aspect of aquaphilic urban design, or water-based imageability (section 3.2.4.). For flood-prone watersheds, canals or linear water features with salient regional structures can be used to unify identifiable features and areas to create more aesthetically, environmentally, and economically coherent cities. These mappable canal patterns facilitate the transformation of inland and upstream suburban and rural land into imageable areas by increasing their water-based familiarity and water-based place identity. Allocentric aquaphilia, which is derived from water-based imageability, should also help build mainstream water-coherent urbanism for public acceptance in inland and upstream areas (section 3.2.4.).

4.5. Greater canal mappability and identifiability for men likely due to evolutionary biology

Compared to women, water contributes more to men's survey knowledge likely because canals tend to be more salient in men's two-dimensional cognitive maps (section 3.3.2.). Men also tend to retain more identifiable canal scenes than women in their spatial memory (section 3.3.1.); however, there is no gender difference in the acquisition of water-based egocentric knowledge for sequencing recognizable landmarks along waterfront edges. These findings may be a reflection of gender differences in evolutionary biology perhaps due to labor division, which predisposes men and women to favor the use of allocentric and egocentric spatial strategies, respectively (Cela-Conde et al., 2009). Compared to women, men may be genetically more inclined to remember the locations of waterscapes in their cognitive maps due to men's higher likelihood in their evolutionary past to use water bodies for nevigating as hunters and gatherers and to collect water from distant territories. In contrast, women were likely exposed to a greater use of egocentric knowledge for arranging non-water objects in a domestic environment (Cela-Conde et al., 2009). Water is therefore not as salient in women's egocentric knowledge as in men's allocentric knowledge (sections 3.3.2 and 3.3.3.).

4.6. Creating an adaptable environment for women with mappable canal structures

No gender difference has been found in dual-perspective spatial memory. This is likely due to the mediating effect of mappable canal configurations on the significant relationship between recognizable canal scenes in cognitive images and the formation of non-water-based survey knowledge (as measured by dual-perspective coherence) (section 3.3.1.). The introduction of more memorable canal configurations helps make a water city more adaptable to women. It is also possible that the gender-sensitive effect of water cannot be properly accounted for by dual-perspective coherence because the measure does not differentiate water from non-water elements on sketch maps (sections 3.3.2. and 3.3.3.). Future research should examine the gender effect on water-based dual-perspective coherence as a comparison for the findings in this study to test this hypothesis.

4.7. Creating an enabling environment for newcomers through mappable canal structures

Albeit gender-invariant, dual-perspective coherence is significantly higher among residents with a greater level of environmental familiarity than visitors. This result provides content validity for dual-perspective coherence as a strong measure of survey knowledge. Compared to visitors, residents' higher survey knowledge may be explained by more salient canal configurations in their two-dimensional cognitive maps (section 3.4.1.). Making canal configurations more memorable in areas with attractions for visitors can potentially make it easier for newcomers to become familiar with unknown territories. Canals with salient regional structures, indicated by the measure of canal mappability, help transform recognizable canal scenes into coherent canal edges, both of which are egocentric in nature and more frequently used by newcomers than residents (sections 3.4.3 and 3.5.3.).

4.8. Creating an adaptable environment for newcomers with more waterscapes

Water-based survey knowledge, or the salience of waterscapes in cognitive maps, does not significantly differ between residents and visitors with less environmental familiarity (section 3.4.2). This result suggests that visitors and residents have a relatively similar level of command of water-based survey knowledge and that cities with more waterscapes are more adaptable to less knowledgeable visitors.

4.9. Mappability as the prerequisite for the identifiability of water-based spatial anchors

Recognizable canal scenes, such as waterfront landmarks and identifiable bridges, help encourage proximity-seeking behaviors toward canals with a coherent two-dimensional structure (section 3.6.). In the absence of mappable canal configurations, distinguishable canal sights are not sufficient for evoking aquaphilic behaviors (section 3.6.1.). Most cities have coherent waterfront edges formed by the clustering of waterfront features and developments; however, if these coherent waterfront edges do not form a noticeable regional configuration as a unified whole, prominent canal scenes in cognitive images alone do not necessarily contribute to the use of canals as water-based spatial anchors. Instead, people’s attachment to canals necessitates a memorable canal arrangement in cognitive maps for making spatial sense of coherent waterfront edges (section 3.7.1.) and identifiable canal views (section 3.6.1. and 3.7.2.). Once mappable canal configurations are in place, canals with more distinguishable scenes are more likely to serve as spatial anchors for self-orientation. These findings suggest that in addition to introducing more salient regional structures for canals, water cities can be made more socially coherent by adding more pedestrian bridges across canals or making canals more visible from the most frequently traversed rights-of-way.

4.10. Limitations and possible future improvements

As a theoretical sampling frame did not exist, a quasi-random sampling approach was used to acquire the participant sample. This convenient sampling approach likely limited the extent to which the results could be generalized beyond the sample. A more rigorous sampling approach should be used to replicate this research design for a greater number of participants and cities to generalize beyond the sample. The degree to which water density influences water-based imageability and water-based goal affordance may need to be further clarified in future research by targeting smaller sites in which the amounts of water and surface areas can be precisely quantified for comparison with their representations on potentially distorted sketch maps to identify potentially substantial differences. This research direction could potentially determine whether water-based imageability is a construct likely to involve more water exposure than water-based goal affordance. This comparison can help determine more nuanced design guidelines, the minimum water density, and the minimum duration of water exposure needed to induce sufficient allocentric aquaphilia for motivating public acceptance of or attraction to water-coherent urbanism.

5. Conclusion

The findings suggest that micro-level relationships between individual perceptions of city image and attachment behaviors to waterscapes as spatial anchors can lead to pro-environmental behaviors, such as people's openness toward water-coherent urbanism.

When inland and upstream cities are made more aesthetically coherent with aquaphilic urbanism, which is characterized in large by mappable canals and identifiable water landmarks, these cities likely become more environmentally, economically, and socially coherent through allocentric aquaphilia via the structuralist influence of aquaphilia on topophilia. The aesthetic coherence of aquaphilic urbanism makes these cities 1) more likely to readily adapt to water-coherent urbanism through the influence of water-based imageability on allocentric aquaphilia; 2) more appealing for new businesses and individuals through the influence of water-based goal affordance on allocentric aquaphilia; and 3) more adaptable to women and newcomers due to a greater presence of visible and mappable canal configurations, coherent waterfronts, and identifiable canal scenes. In Lynch's terms, water-centric cities are imageable because of the salient structures of water-based paths (as canals), the continuity of edges along waterfronts, and the salient scenes of water-based landmarks along canals. This aesthetic coherence of water urbanism assists psychological integration due to greater emotional coherence. This motivational pull may provide a self-organizing bottom-up momentum to make cities more environmentally, economically, and socially coherent.

CHAPTER VI

TOWARD AN ICONOGRAPHY OF WATER URBANISM

1. Aesthetic, Emotional, Environmental, and Social Coherence of Water Urbanism

Overall, in Chapter II the author utilized urban design attributes and environmental affordances to conduct content analyses of qualitative field data to inform research designs and measures used in subsequent chapters. In Chapter III, the author employed regression analyses to operationalize water-based aesthetic coherence with urban picturesque theories from Appleyard and Lynch to examine the image of a pluralist water city. In Chapter IV, the author conducted a path analysis to substantiate a composite model of social-psychological and environmental-psychological theories of attachment. This composite model helped inform a possible theory of aquaphilic urbanism for connecting the aesthetic and emotional aspects of water-based coherence. In Chapter V, the author empirically tested the relationships among all variables from previous chapters, and introduced openness toward water-coherent urbanism as a measure for water-based environmental coherence. This chapter identified measures of water-based aesthetic coherence as a mediator between water density/watershed location and water-based emotional coherence. In addition, the author found mediating effects of water-based emotional coherence measures on the relationship between water-based aesthetic coherence and water-based environmental coherence. Canal mappability was also substantiated as a mediator for the effects of gender or the group variable of visitors or residents on coherence measures. This finding suggests the potential of canal mappability in facilitating social coherence in a water-centric city.

2. Inter-chapter Connections

In Chapter II, the author used urban design attributes and affordances as an evaluative category to calculate weighted frequency totals from the following field data from 60 participants: 1) their likes or dislikes regarding existing water networks, 2) their reasons for recollecting cognitive mapping features, and 3) their explanations for recalling photovoice features. The author weighted response frequencies with the sequence in which the participants recalled their responses. Chapter II qualitatively explored how aquaphilia interacted with the perceived urban design quality of water-based spatial anchors to contribute to the imageability of water-centric cities. Pictorial aquaphilia was often the most or second most frequently mentioned reason for recalling several waterscape types in cognitive mapping and photovoice protocols. The findings suggest that the contribution of waterscape attachment to coherence measures overlaps with those derived from waterscape mappability and identifiability.

Chapter II provided the following directions for quantitative research: 1) to account for its possible contributions to the aesthetic coherence of the city image, aquaphilia—in the sense of innate human affection toward safe and clean waterscapes—should be included in waterscape mappability and identifiability processes as waterscape attachment; 2) cognitive mapping and photovoice, as recall protocols, should be complemented with interview questions to measure how aquaphilia and urban design attributes affect people's acquired attachment to water-based spatial anchors and water-centric cities; 3) both water-based and non-water-based coherence measures should be used to study whether water is the sixth element of imageability.

The first research direction informed the inclusion of aquaphilia sensitivity baseline in the regression models in Chapter III and the path analysis model in Chapter IV. As aquaphilia sensitivity baseline was significant in both Chapters III and IV, it was included in all mediation analysis models in Chapter V. The second research direction derived from Chapter II confirmed that a mixed-methods research design using both visual and nonvisual recall protocols was necessary for generating measures for waterscape mappability, identifiability, and attachment in Chapter III and indicators for the constructs of aquaphilic urbanism and water-based place attachment in Chapter IV. Chapter II also revealed that the five waterscape types were distinctively different. Thus, Chapter III applied the three waterscapes components—that is, mappability, identifiability, and attachment—to these five waterscape types to generate 15 possible waterscape models for studying Lynch's three components and five elements of imageability in water-centric cities. The third research direction inspired the use of water-based and nonwater-based coherence measures as regression dependent variables in Chapter III. The comparison of regression results indicates that water was likely the sixth element of imageability.

Chapter III investigated the how waterscapes contributed to the perceived aesthetic coherence of a water city image for both visitors and residents with varying aquaphilia sensitivity baselines and socioeconomic backgrounds, including gender, age, education, and income. Sketch map coherence measures were used as dependent variables for regression analyses while the allocentric, egocentric, and emotional salience of waterscapes—namely, waterscape mappability, identifiability, and attachment—and socioeconomic backgrounds of participants were employed as independent variables.

Inter-rater reliability tests were conducted to derive reliable coherence measures based on the average ratings of two independent raters. These ratings were obtained from the use of a rubric and survey questions to evaluate sketch maps. Chapter III identified possible mediators of the effect of gender or the group variable of visitors or residents on coherence measures. These mediators were tested in mediation analyses in Chapter IV.

Chapter IV used the anchorpoint theory to combine environmental-psychological and social-psychological theories of attachment into a composite model. The author conducted a nested path analysis choose this composite model over the environmental-psychological and social-psychological models of attachment as competing hypotheses. As water was substantiated as a sixth element of imageability in Chapter III, measures for all waterscape types were aggregated to measure water-based constructs for a water-based sense of place using the indicators suggested in Chapter II. Specifically, water-based familiarity was generated from all waterscape mappability measures, water-based place identity from all waterscape identifiability variables, and water-based place attachment from all waterscape attachment indicators. While aquaphilia sensitivity baseline from Chapter III was repurposed into water-based comfort, the extent to which water helped with self-orientation was proposed as a measure for water-based orientation, because legibility was identified as an intrinsic attribute associated with people's liking for water-based spatial anchors in Chapter II.

The results from Chapter IV indicate that aquaphilic urbanism as a water-based sense of place can be operationalized into water-based familiarity, water-based comfort, water-based identifiability, and water-based orientation to evoke water-based place attachment in the sense of the influence of allocentric aquaphilia on topophilia. In addition, a possible higher construct, which the author refers to as water-based imageability or water-based symbolic attachment, may explain water-based familiarity and water-based identifiability. Similarly, the author also alludes to water-based goal affordance or water-based functional attachment as another possible higher construct underlying water-based comfort and water-based orientation. In Chapter V, the investigator conducted principal components analyses to confirm whether these two constructs parsimoniously explained their respective measures. Thereafter, water-based imageability and water-based goal affordance were tested as potential mediators between water density/watershed location as the independent variable and water-based place attachment or openness toward water-coherent urbanism as the dependent variable to study the relationship among aesthetic, emotional, and environmental coherence of water-centric cities.

3. Methodological Contributions

3.1. Methodological gaps

3.1.1. Methodological issues in spatial cognition research

Because spatial cognition studies are primarily interested in investigating group differences in spatial abilities, these studies have often used only three categories of spatial knowledge with survey knowledge as the most advanced state of spatial comprehension (Thorndyke and Hayes-Roth, 1982; Münzer et al., 2006). However, many sketch maps classified under survey knowledge are not imageable. The three-category classification is not sufficiently descriptive to distinguish imageable cognitive maps from nonimageable ones. Furthermore, most spatial cognition studies did not control for the influences of varying individual graphic production skills on sketch map coherence.

Although many people with good wayfinding abilities have trouble drawing sketch maps (Clayton and Woodyard, 1981; Downs and Siegel, 1981; Lewis, 1976; Hart, 1981), most urban picturesque studies have rarely resorted to a nongraphic method for probing participants' spatial knowledge. In contrast, spatial cognition researchers (Golledge and Stimson, 1997; Kirasic, Allen, and Siegel, 1984) tend to use nonsketch-map-based quantitative measures and undervalue the topological information in sketch maps, because these maps can be metrically inaccurate and these researchers are usually not as interested in environmental configuration as spatial ability.

3.1.2. Methodological pitfalls in urban picturesque research

Urban picturesque researchers have not devised a method to integrate Appleyard's (1970) topological analysis of sketch maps with Lynch's (1960) frequency analysis of sketch map features. Appleyard's (1970) concern for structuring a pluralistic city has been disconnected from Lynch's (1960) enthusiasm for creating an imageable city. In addition, Lynch (1960) did not explicitly relate his definition of imageability with his five elements and three components of imageability to provide guidance on how these elements and components can be composed into an imageable city.

Furthermore, most previous urban picturesque studies have not adequately addressed the issues of validity, reliability, and generalizability. For example, it is unclear whether the results of Appleyard's (1970) research for structuring a pluralistic city and Lynch's (1960) theory of imageability were influenced by their subjective judgments or generalizable beyond the city under study. These urban picturesque methods have largely been data driven and have not explicitly incorporated more rigorously tested theories from spatial cognition research that employs experimental designs.

3.1.3. Methodological limitations in place attachment research

Although many place researchers use Likert scales to measure constructs for functional attachment, symbolic attachment has largely been measured using statements of beliefs or perceptions based on environmental features that have been preselected by researchers (Stedman, 2003; Jorgensen and Stedman, 2001; Williams and Vaske, 2003). As place research tends to be conducted by psychologists, their focus has been primarily on developing scales to measure attitudes for multi-site projects. The environmental features in these studies have remained limited in terms of description and their ecological validity in linking place attachment with place-making has been compromised.

3.2. A robust sketch map evaluative rubric sensitive to topological implications for design

3.2.1. Eight-stage rubric for urban picturesque studies

To address these methodological limitations, Chapter III tested the inter-rater reliability of both the three-stage and eight-stage classifications of spatial comprehension for the sketch map evaluative rubric. The three-stage rubric was eliminated because it did not have adequate inter-rate reliability, while the eight-stage rubric was selected due to its satisfactory inter-rater reliability. This suggests that using survey knowledge as an overarching category for advanced spatial knowledge is inadequate for imageability research. In other words, the research substantiated the feasibility of an eight-stage sketch map evaluative rubric for urban picturesque studies.

3.2.2. Twelve-stage rubric for controlling differences in graphic production skills

The author also added four additional stages to the eight-stage classification to control for differences in individual graphic production skills. This twelve-stage rubric also had adequate inter-rater reliability. However, the eight-stage rubric was chosen over the twelve-stage rubric because the coherence measure generated from the eight-stage rubric resulted in a higher R^2 value when it was used for the regression-dependent variable in the presence of both environmental and socioeconomic backgrounds of participants as independent variables. This study demonstrated the feasibility of site- and sample-specific methods for controlling the differences in graphic production skills.

3.2.3. Content validity of rubric categories and variables for urban picturesque studies

Compared with Appleyard's (1970) sketch map scoring method derived from a topological assessment of collected sketch maps, the eight-stage classification of spatial knowledge imbues the sketch map evaluative rubric with a greater level of content validity. Specifically, these rubric categories as developmental stages of spatial knowledge were used to generate rubric-based indicators—including hierarchical coherence, topological coherence, configurational coherence, and projective coherence—for triangulation with coherence and waterscape variables. This triangulation provides these variables with a greater level of content validity, and empirically connects urban picturesque with spatial cognition theories.

3.3. A more reliable and generalizable multi-sited mixed-methods research design

While Appleyard did not test the inter-rater reliability of his classification of sketch maps using his empirically derived rubric, this study tested the inter-rater reliability of all measures generated from this theory-informed scoring rubric. This method can be used to fine-tune the rubric in the future with a greater number of cities and a larger sample of participants to make it as reliable and generalizable as possible for used in multi-sited mixed-methods research designs.

3.3.1. Triangulation of urban picturesque methods and theories to generate design guidelines

The regression models in Chapter III provided a feasible multi-sited research design to operationalize Lynch's definition of imageability with a theoretically informed and empirically tested sketch map rubric. Thereafter, this topological analysis of a sketch map was triangulated with measures for Lynch's components and elements of imageability derived from frequency analysis of recall elements to account for the components as both allocentric and pictorial perspectives and the elements as waterscape types. The regression analysis also permitted controlling for the socioeconomic backgrounds of participants, thereby enabling researchers to study how aspects of imageability mediate group differences in spatial comprehension to inform possible ways to design a more coherent public realm for a pluralistic city.

3.3.2. A mixed-methods research design for producing urban picturesque design guidelines

Most importantly, the use of a mixed-methods research design—which includes cognitive mapping, photovoice, and emotional recall protocols—helped to connect Lynch's structure, identity, and meaning—that is, his three components of imageability—with spatial cognition theories, including the notion of spatial anchor based on the anchorpoint theory and the dual perspectives of spatial knowledge. By asking participants to follow up with a reason for recalling each feature, researchers can conduct content analysis to better understand the nature of a component or element of imageability and a spatial anchor in a specific frame of reference. Compared to psychologists' methods for measuring symbolic attachment with statements of attitude to develop scales for multi-sited research, the recall protocols enable more ecologically valid environmental features to emerge as allocentric, pictorial, and emotional anchors for structure, identity, and meaning. This mixed-methods research design, when applied to a larger number of cities and participants, could potentially produce generalizable design guidelines for testing using quantitative methods in the future.

4. Theoretical Contributions

4.1. Connecting the anchorpoint theory and the social-psychological theory of attachment

4.1.1. Equal salience of water-based spatial anchors in residents' and visitors' cognitive maps

Chapter IV empirically supported a possible theoretical connection between the anchorpoint theory in behavioral geography and the social-psychological theory of attachment. Chapter V showed that dual-perspective coherence was significantly higher for residents than visitors. In contrast, water-based survey knowledge—the salience of waterscapes as spatial anchors in cognitive maps—did not significantly differ between residents and visitors. This result suggests that water-based spatial anchors are likely to be equally salient in the cognitive maps of both residents and visitors.

4.1.2. Increasing cities' adaptability to newcomers with more water-based spatial anchors

In addition, cities with more water-based spatial anchors could be more adaptable for less spatially knowledgeable newcomers, because these water-based spatial anchors help them self-orient in unknown territories and organize spatial information. Chapter V also revealed that canal mappability fully mediated the significant group effect of visitor and resident on dual-perspective coherence with a marginal significance. Specifically, canals with salient regional structures helped to transform recognizable canal scenes into coherent canal edges, both of which were egocentric in nature and more frequently used by newcomers than residents.

4.1.3. Empirical evidence for dominance of egocentric perspective among newcomers

Overall, the findings helped substantiate the following theories regarding the development of spatial knowledge: During the first environmental exposure, newcomers may revert to a preoperational level of spatial comprehension (Golledge and Stimson, 1997). This preoperational level of spatial knowledge has been postulated to be dominated by egocentric controls that are characteristic of the developmental period from approximately two to seven years of age when interpersonal attachment is developed (Piaget and Inhelder, 1967).

4.1.4. Increasing cities' imageability and adaptability with the structural salience of canals

The results contributed to the theory of structuring a pluralistic city and the theory of imageability. Specifically, canals with salient regional structures were found to jumpstart the allocentric coherence of cognitive maps for newcomers with a tendency to revert to the egocentric mode of spatial comprehension and for women who tend to favor the egocentric frame of reference more often than men do. Canal mappability increased the extent to which cities can become imageable and, thus, made cities more adaptable to newcomers and women.

4.2. Linking the environmental-psychological and social-psychological theories of attachment

4.2.1. Water-based spatial anchors as salient loci of attachment

While Chapters III and V found that allocentric aquaphilia may be instinctual human attachment to water-based spatial anchors that influence the aesthetic coherence of city image, Chapter IV empirically substantiated the nature of water-based spatial anchors as salient features that provide a sense of familiarity and comfort to motivate proximity-maintenance behaviors and a sense of identifiability and orientation to evoke the allocentric influence of aquaphilia on topophilia, which is a form of water-based place attachment.

4.2.2. A potential social-environmental-psychological model of attachment

Chapter IV revealed the contributions of water-based spatial anchors to participants' emotional coherence with water-centric cities as constructs from both the environmental-psychological and social-psychological theories of attachment. Chapter IV showed that this combined theory was a better fitting model than either theory alone in explaining how water-based spatial anchors contributed to water-based place attachment in a water-centric city. This result could potentially help to advance the theory of place attachment if the same model can be applied to nonwater-centric cities and recall frequencies can be tallied based on Lynch's elements of imageability or actual spatial anchors of the highest order in these cities.

4.3. Connecting place-making with place-bonding

4.3.1. Empirical evidence for linking place-making with place-bonding through aquaphilia

There has been little empirical evidence for linking place-making with place-bonding (Lewicka, 2011). An increasing number of place attachment studies have focused on investigating the processes of place attachment with a specific water body as an influential factor in developing a sense of place or people's intrinsic connectedness with nature in a specific locality. Although the presence of water has been found to contribute to topophilia (Ogunseitan 2005), there is a lack of literature on how water can be systematically integrated into an environment to affect topophilia. This research provided cursory evidence for linking place-making and place attachment in water-centric cities through the connections among pictorial, egocentric, and allocentric aquaphilia.

4.3.2. Confirming water as a sixth element of imageability due to pictorial aquaphilia

In Chapter II, the author referred to Lynch's imageability as a coherent structure of physical arrangements of elements that evoke a strong image and identity. This nonperspective aspect of (waterscape-specific) imageability seemed to be the most common reason underlying the allocentric recall salience of canals as spatial anchors, followed by rivers, harbors, and water landmarks. In contrast, (waterscape-specific) imageability was only the fourth most frequently mentioned urban design attribute for lakes after complexity, pictorial aquaphilia, and accessibility. Compared with other waterscape types, the (elemental) imageability of canals contributed the most to their significance as spatial anchors in cognitive maps.

For the cognitive mapping recall protocol, aquaphilia was the second most frequently mentioned reason for recalling both lakes and harbors. Aquaphilia was as frequently stated as accessibility as a reason for recalling canals. The imageability of harbors seemed to be associated with their large sizes. For the photovoice recall protocol, aquaphilia was the most commonly mentioned cause for recalling harbors and the second most frequent reason for recalling lakes and canals. Aquaphilia was almost as frequently stated as accessibility as a reason for recalling lakes. Pictorial aquaphilia as instinctual human attachment to clean and safe water scenes was likely to have an undeniable influence on the imageability of water-centric cities as well as the pictorial coherence of lakes and harbors and their salience as identifiable scenes.

By comparing results using water-based and nonwater-based coherence measures as regression dependent variables, Chapter III confirms that water may be distinctively different from and more cognitively powerful than conventional elements of imageability, which are paths, landmarks, nodes, edges, and districts.

4.4. Operationalizing and empirically testing imageability

In Chapter III, the author discovered that the dual-perspective coherence of water urbanism, as measured by the sketch map rubric, was significantly associated with water landmark identifiability as well as the mappability of rivers and canals. This finding suggests that the imageability of a water city can be characterized as the juxtaposition of the identity component from the element of water landmarks and the structure component from the elements of water edges and paths. This empirically derived definition of imageability for water urbanism confirms Lynch's premise that an association can be more readily made among identifiable, rather than undifferentiated, urban landscape forms (Lynch, 1990). This result is also consistent with the general urban picturesque literature related to the dual aspect of coherence, which allows the eye to rest on prominent objects as a pattern of continual guidance to connect one contrasting element with another, thereby facilitating the mind to form associations (Beardsley, 1958; Isaacs, 2000; Raynsford, 2011). Although this study focused on water-centric environments, its results seemed to be in line with Lynch's general theory of imageability. This observation suggested that the research design can be adopted for a nonwater-based environment by classifying responses using Lynch's components and elements of imageability.

5. Practical Contributions

This research resulted in the following design implications as possible guidelines for an iconography of water urbanism. These guidelines can potentially enable cities to become more coherent by retrofitting their public realm with waterscapes.

5.1. Locating water landmarks by district-defining continuous edges and clusters of landmarks

As shown in Chapter III, water landmark identifiability is likely related to topological knowledge. According to the definitions of topological knowledge in the sketch map rubric, the identifiability of water landmarks, such as waterfront landmarks or bridges, is potentially associated with the delineation of a district or multiple districts based on clusters of landmarks or continuous edges formed by landmarks. This result indicates that water landmarks are made identifiable possibly due to the presence of district-defining features, such as continuous edges or clusters of landmarks. Urban designers may consider locating waterfront landmarks or bridges in locations with continuous waterfront edges and clusters of landmarks to maximize their potential to be identifiable and, thus, their contribution to the coherence of city image.

5.2. Introducing canals as a salient configuration encompassing multiple distinct forms

Similarly, the association between canal mappability and configurational knowledge suggests that canal mappability is likely to be related to a single configuration as a collective pattern greater than the sum of multiple distinct forms. This result implies that retrofitting existing straight streets with canals or waterways—as in the case of the Gheonggyecheon stream restoration project in Seoul, Korea—may not maximize the potential of canals to contribute to the coherence of city image. Designers should strive to combine street right-of-ways with public open spaces to create a salient canal configuration comprising multiple distinct forms, like the concentric rings of canals in Amsterdam.

5.3. The image of the water city for aquaphilic urbanism and water-coherent urbanism

Chapter V suggested that to motivate public acceptance of water-coherent urbanism, inland and upstream cities need to focus on water-based imageability by increasing the mappability and identifiability of waterscapes. Increasing the extent to which water helps with stress regulation and orientation alone is not sufficient. These cities could consider retrofitting their upstream suburbs with structurally salient canals or prioritize the implementation of these canals in identifiable urban areas with recognizable features. Such design strategies could help to increase the imageability of these cities to evoke water-based place attachment for facilitating individuals' environmental adaptation and adapting upstream and inland cities to water-coherent urbanism.

5.4. Water-based spatial anchors for environmental adaptation

Chapter V showed that water-based goal affordance did not support further application of water-coherent urbanism through allocentric aquaphilia. However, it mediated the indirect effect of watershed location or water density on allocentric aquaphilia more effectively than water-based imageability. This result suggests that, urban design can still evoke allocentric aquaphilia through the use of local waterscapes as water-based spatial anchors that facilitate stress reduction and ease self-orientation. These attractive local waterscapes may help contribute to environmental adaptation through the structuralist influence of aquaphilia on topophilia. Future research should investigate how to design these waterscapes to better help with stress reduction and wayfinding with less consumption of land and water.

5.5. Prioritizing mappable canal structures over recognizable canal scenes

Chapter V indicated that in the absence of mappable canal configurations, distinguishable canal sights are not sufficient for evoking such aquaphilic behaviors. Instead, people's attachment to canals necessitates a memorable canal arrangement in cognitive maps first as spatial anchors in order to make sense of coherent waterfront edges and identifiable canal views. Once mappable canal configurations are established, canals with more distinguishable scenes are more likely to serve as spatial anchors for self-orientation.

6. Limitations and Possible Future Improvements

6.1. Investigating construct and data validity with group-invariant testing

Although the power analysis revealed that the sample size was adequate, a larger sample size could enable the use of group-invariant testing of the path coefficients in Chapter IV. Specifically, by employing two randomly split subsamples to test the same model, it is possible to test both construct validity and data validity. Another similar test can also be conducted to ascertain if path coefficients differ significantly between

between high and low water density cities. If so, it may be necessary to include a group variable of high and low density water cities in the model reported in Chapter IV.

6.2. Developing scales for expanding the path model with measurement variables

The results from Chapter II's content analyses can be used to identify specific environmental attributes or features as elements of imageability to generate statements of beliefs and attitudes for testing possible scales for use with a larger sample. This improvement adds measurement variables to the constructs used by the path model's structural variables in Chapter IV in order to increase the validity and reliability of each construct with factor analysis. In addition, to test the applicability of this model beyond water-centric environments, water-based and nonwater-based measures may be generated from participants' responses to compare the relative contributions of water-based and nonwater-based elements of imageability to model constructs.

6.3. Spatially stratified sampling for a greater number of cities and participants

Because a theoretical sampling frame did not exist, the author employed a quasi-random sampling approach to recruit participants. This convenient sampling approach limited the extent of generalizability of the results beyond the existing sample. A more rigorous sampling approach, such as spatially stratified sampling, should be used to replicate this research design for a greater number of participants and cities to make the results more generalizable.

6.4. Making the sketch map evaluative rubric more robust and generalizable

The complexity of eight- and twelve-stage rubrics makes it difficult to use them for a larger sample of participants as raters. However, for imageability research, the three-stage rubric was not adequate for capturing sufficient morphological nuances in sketch maps.

Future research may consider testing whether the component and relation can be combined for each spatial knowledge category to reduce eight-stage to four-stage and twelve-stage to six-stage. This modification to the rubric may make it more accessible for testing in more water-centric cities with a larger number of raters to make it more robust and generalizable.

7. Possible Future Research Directions

7.1. Studying aquaphilia with psychophysiological measurements and experience recording

Future research should investigate aquaphilia on smaller sites with the use of specific spatial-temporal recording of environmental experience, eye-tracking data, and psychophysiological measurement. Researchers should also measure participants' psychophysiological baselines and obtain pre- and post-experience behavioral measures using the same cognitive mapping, photovoice, and emotional recall measures. By simultaneously recording participants' psychophysiological measurements and eye-tracking data, researchers can better differentiate changes in psychophysiological measurements due to visual fixations on water-based versus nonwater-based environmental features.

7.2. Testing alternative relationships between coherence and aquaphilia sensitivity baseline

Chapter III found that lower allocentric and egocentric coherence levels were found to be associated with a higher aquaphilia sensitivity baseline, that is, the extent to which water helps with stress regulation. Acquiring participants' before and after psychophysiological baselines and behavioral measures can enable researchers to test the following competing hypotheses: 1) stress-prone populations tend to seek out water features as spatial anchors to reduce navigation anxiety because they are more likely to be spatially challenged; or 2) due to greater navigation anxiety, those who are spatially challenged tend to have a greater need for stress regulation and are more likely to approach water to reduce stress.

7.3. Examining the effects of water quantity, exposure duration, and location on imageability

Chapter II showed that imageability related to harbors seems to be associated with their large sizes and resultant visibility on a map. The imageability of lakes could potentially be related to their central locations in cities. By choosing study sites with varying amounts and locations of waterscapes, this spatial-temporal research design can also be utilized to study the effect of water quantity, duration of water exposure, and location of waterscapes on the sense of familiarity, comfort, orientation, and identifiability, as well as on water-based place attachment.

7.4. Investigating the effects of water densities on water-based imageability and goal affordance

The degree to which water density influences water-based imageability and water-based goal affordance requires further investigation. Future research may target smaller sites where the amounts of water and surface areas can be precisely quantified and compared to their representations on potentially distorted sketch maps. This research direction could potentially shed light on whether water-based imageability is a construct that is likely to involve more water exposure than water-based goal affordance to help determine more nuanced design guidelines, minimum water density, and the minimum duration of water exposure required to induce sufficient allocentric aquaphilia for motivating public acceptance of water-coherent urbanism.

7.5. Testing the effects of scale on research design and model performance

The spatial cognition of a water-centric environment may differ significantly between a site and city-scale investigation. This research design can be used to study possible ways to quantify the amount of water on sketch maps and relate this information to the actual amount of water in the environment to control possible topological distortions in sketch maps. This control mechanism may be applied to a city scale to quantify the amount of water that is represented in sketch maps and its contribution to sketch map coherence measures. The duration of water exposure required to generate a water-based sense of place may inform the length of linear waterscapes in right-of-ways of cities where people are not able to dwell. In addition, the locational effects of waterscape should also be studied in cities containing waterscapes with a wide range of locations.

7.6. ***Comparing efficiency of spatial acquisition through maps versus environmental exposure***

In Chapter III, canal mappability was the only significant effect of water urbanism for all three allocentric coherence measures based on map identifiability, including uncolored, colored, and water-based allocentric coherence. Canal mappability was also found to be associated with configurational knowledge. Although education was used as a proxy variable to control for exposure to maps and secondary information, it was not clear whether visitors' allocentric knowledge of city image was jumpstarted by the salient structures of canals observed from maps or direct environmental experience. Future research should establish comparison groups using either two-dimensional maps or a visual reality walk-through to present a wide range of regional structures of linear elements to assess the relative efficiency of each method of spatial acquisition and identify topological principles for creating salient regional structures. This research design could also be used to study the impacts of length, width, curvature, and location on the imageability of linear waterscapes.

APPENDIX A

BRIEFING MATERIALS FOR THE FIRST SKETCH MAP EVALUATION SURVEY USING RUBRIC ONE

Table 1. Proposed rubric one for sketch map evaluation

Please select one statement that best describes the sketch map. This sketch map appears to…
1. show randomly distributed landmarks/nodes with few path connections or an impressionist sketch of landmark characteristics.
2. illustrate an interrelated system of landmarks and nodes with few path connections.
3. display few path segments to connect nodes and landmarks as if drawn from turn-by-turn navigation instructions.
4. exhibit a network of interrelated paths, making route improvisation possible.
5. reveal distinct landmark/node clusters around anchor points (major landmarks).
6. demonstrate a nested hierarchy of landmark/node clusters around anchor points.
7. delineate districts by continuous edges or the clustering of landmarks/nodes.
8. show a nested hierarchy of multiple districts.
9. indicate a distinct form that resembles only a small part of the city center.
10. capture the city structure as an identifiable configuration that can be easily recalled without looking at the map.
11. conjecture abstract components from known topological or configurational components.
12. infer abstract relationships from known topological or configurational relationships .

Briefing Materials for the First Sketch Map Scoring Rubric

From *The City image and Its Elements by* Lynch (1960, 46-49)

"There seems to be a public image of any given city which is the overlap of many individual images. Or perhaps there is a series of public images, each held by some significant number of citizens. Such group images are necessary if an individual is to operate successfully within his environment and cooperate with his fellows. Each individual picture is unique, with some content that is rarely or never communicated, yet it approximates the public image, which, in different environments, is more or less compelling, more or less embracing.

This analysis limits itself to the effects of physical, perceptible objects. There are other influences on imageability, such as the social meaning of an area, its function, its history, or even its name. These will be glossed over, since the objective here is to uncover the role of form itself. It is taken for granted that in actual design form should be used to reinforce meaning, and not to negate it. The contents of the city images so far studied, which are referable to physical forms, can conveniently be classified into five types of elements: paths, edges, districts, nodes, and landmarks. Indeed, these elements may be of more general application, since 1hey seem to reappear in many types of environmental images, as may be seen by reference co Appendix A. These elements may he defined as follows:

l. *Paths*. Paths are the channels along which the observer customarily, occasionally, or potentially moves. They may be streets, walkways, transit lines, canals, railroads. For many people, these are the predominant elements in their image. People observe the city while moving through it, and along these paths the other environmental elements are arranged and related.

2. *Edges*. Edges are the linear elements not used or considered as paths by the observer. They are the boundaries between two phases, linear breaks in continuity: shores, railroad cuts, edges of development, walls. They are lateral references rather than coordinate axes. Such edges may be barriers, more or less penetrable, which close one region off from another; or they may be seams, lines along which two regions are related and joined together. These edge elements, although probably not as dominant as paths, are for many people important organizing features, particularly in the role of holding together generalized areas, as in the outline of a city by water or wall.

3. *Districts*. Districts are the medium-to-large sections of the city, conceived of as having two-dimensional extent, which the observer mentally enters "inside of," and which are recognizable as having some common, identifying character. Always identifiable from the inside, they are also used for exterior reference if visible from the outside. Most people structure their city to some extent in this way, with individual differences as to whether paths or districts are the dominant elements. It seems co depend not only upon the individual but also upon the given city.

4. *Nodes*. Nodes are points, the strategic spots in a city into which an observer can enter, and which are the intensive foci co and from which he is traveling. They may be primarily junctions, places of a break in transportation, a crossing or convergence of paths, moments of shift from one structure to another. Or the nodes may be simply concentrations, which gain their importance from being the condensation of some use or physical character, as a street-corner hangout or an enclosed square. Some of these concentration nodes are the focus and epitome of a district, over which their influence radiates and of which they stand as a symbol. They may be called cores. Many nodes, of course, partake of the nature of both junctions and concentrations. The concept of node is related to the concept of path, since junctions are typically the convergence of paths, events on the journey. It is similarly related to the concept of district,
since cores are typically the intensive foci of districts, their polarizing center. In any event, some nodal points are to be found in almost every image, and in certain cases they may be the dominant feature.

5. Landmarks. Landmarks are another type of point-reference, bur in this case the observer does not enter within them, they are external. They are usually a rather simply

defined physical object: building, sign, store, or mountain. Their use involves the singling out of one element from a host of possibilities. Some landmarks are distant ones, typically seen from many angles and distances, over the tops of smaller elements, and used as radial references. They may be within the city or at such a distance that for all practical purposes they symbolize a constant direction. Such are isolated rowers, golden domes, and great hills. Even a mobile point, like the sun, whose motion is sufficiently slow and regular, may be employed. Other landmarks are primarily local, being visible only in restricted localities and from certain approaches. These are the innumerable signs, storefronts, trees, doorknobs, and other urban derail, which fill in the image of most observers. They are frequently used clues of identity and even of structure, and seem to be increasingly relied upon as a journey becomes more and more familiar.

The image of a given physical reality may occasionally shift its type with different circumstances of viewing. Thus an expressway may be a path for the driver, and edge for the pedestrian. Or a central area may be a district when a city is organized on a medium scale, and a node when the entire metropolitan area is considered. But the categories seem to have stability for a given observer when he is operating at a given level.

None of the element types isolated above exist in isolation in the real case. Districts are structured with nodes, defined by edges, penetrated by paths, and sprinkled with landmarks. Elements regularly overlap and pierce one another. If this analysis begins with the differentiation of the data into categories, it must end with their reintegration into the whole image. Our studies have furnished much information about the visual character of the element types. This will be discussed below. Only to a lesser extent, unfortunately, did the work make revelations about the interrelations between elements, or about image levels, image qualities, or the development of the image. These latter topics will be treated at the end of this chapter."

From *Spatial Behavior – A Geographic Perspective by* Golledge and Stimson (1997, 167)

5.6.3. Anchorpoint Theory and Knowledge Hierarchies

This characterization closely resembles the anchorpoint theory suggested by Golledge (1975, 1978b), in which a hierarchical ordering of locations, paths, and areas within the general spatial environment is based on the relative significance of each to the individual. Initially locations that are critical in the interaction process - such as home, work, and shopping places - anchor the set of spatial information developed by an individual and condition the search for paths through segments of space capable of connecting the primary nodes or anchorpoints. Both node and path knowledge is organized hierarchically with primary, secondary, tertiary, and lower-order nodes and paths forming a skeletal structure upon which additional node, path, and areal information is grafted . Home, work, and shopping tend to serve as the initial primary nodes and are among the major anchorpoints from which the rest of the hierarchy develops. Other anchorpoints may include commonly recognized, known, and often-used places in the environment.

A total set of anchorpoints then is a combination of those selected in common with others as part of a general pattern of recognition of critical things in an environment (i.e., the common cues that identify cities as being distinct one from another), together with the principal idiosyncratic sets of points at are relevant to any single individual's activity patterns. As interactions occur along the paths between the primary nodes, there is a

spillover or spread effect and the development of the concepts of neighborhood, community, region, and so on. Neighborhoods surrounding the primary node sets become known first, and continued interactions along developing node-path networks strengthen the image of segments of the environment for each individual at the same time as they formalize the content and order
of the basic common knowledge structure."

Topological. Merriam-Webster Dictionary defines topological as involving configurational properties (i.e. continuity, connectivity, and proximity) unaltered under elastic deformation by continuous planes such as stretching or twisting. For instance, circle, triangle, and square can be considered topologically identical because they are all formed by a continuous line with conjoined beginning and end points to separate a space into inside and outside areas. Topological component thus introduces aerial concepts of districts, while declarative component implies the point nature of a landmark or node and procedural component refers to the linear nature of a path.

Configurational. According to Merriam-Webster Dictionary, configurational means being characterized by configuration or a distinctive form. The dictionary defines configuration as a *figure* or *pattern* resulting from *relative* arrangement of parts or elements. Configuration has also been equated with gestalt that is more than the sum of its parts. This study thus uses configurational to refer to the wholeness of a figure or pattern as an entity that is more than a collection of declarative, procedural, and topological components and relations.

APPENDIX B

REVISED BRIEFING MATERIALS FOR THE SECOND SKETCH MAP EVALUATION SURVEY USING RUBRIC TWO

From *The City image and Its Elements by* Lynch (1960, 46-49)

“There seems to be a public image of any given city which is the overlap of many individual images. Or perhaps there is a series of public images, each held by some significant number of citizens. Such group images are necessary if an individual is to operate successfully within his environment and cooperate with his fellows. Each individual picture is unique, with some content that is rarely or never communicated, yet it approximates the public image, which, in different environments, is more or less compelling, more or less embracing.

This analysis limits itself to the effects of physical, perceptible objects. There are other influences on imageability, such as the social meaning of an area, its function, its history, or even its name. These will be glossed over, since the objective here is to uncover the role of form itself. It is taken for granted that in actual design form should be used to reinforce meaning, and not to negate it. The contents of the city images so far studied, which are referable to physical forms, can conveniently be classified into five types of elements: paths, edges, districts, nodes, and landmarks. Indeed, these elements may be of more general application, since they seem to reappear in many types of environmental images, as may be seen by reference to Appendix A. These elements may he defined as follows:

l. *Paths*. Paths are the channels along which the observer customarily, occasionally, or potentially moves. They may be streets, walkways, transit lines, canals, railroads. For many people, these are the predominant elements in their image. People observe the city while moving through it, and along these paths the other environmental elements are arranged and related.

2. *Edges*. Edges are the linear elements not used or considered as paths by the observer. They are the boundaries between two phases, linear breaks in continuity: shores, railroad cuts, edges of development, walls. They are lateral references rather than coordinate axes. Such edges may be barriers, more or less penetrable, which close one region off from another; or they may be seams, lines along which two regions are related and joined together. These edge elements, although probably not as dominant as paths, are for many people important organizing features, particularly in the role of holding together generalized areas, as in the outline of a city by water or wall.

3. *Districts*. Districts are the medium-to-large sections of the city, conceived of as having two-dimensional extent, which the observer mentally enters "inside of," and which are recognizable as having some common, identifying character. Always identifiable from the inside, they are also used for exterior reference if visible from the outside. Most people structure their city to some extent in this way, with individual differences as to whether paths or districts are the dominant elements. It seems co depend not only upon the individual but also upon the given city.

4. *Nodes*. Nodes are points, the strategic spots in a city into which an observer can enter, and which are the intensive foci co and from which he is traveling. They may be primarily junctions, places of a break in transportation, a crossing or convergence of

paths, moments of shift from one structure to another. Or the nodes may be simply concentrations, which gain their importance from being the condensation of some use or physical character, as a street-corner hangout or an enclosed square. Some of these concentration nodes are the focus and epitome of a district, over which their influence radiates and of which they stand as a symbol. They may be called cores. Many nodes, of course, partake of the nature of both junctions and concentrations. The concept of node is related to the concept of path, since junctions are typically the convergence of paths, events on the journey. It is similarly related to the concept of district, since cores are typically the intensive foci of districts, their polarizing center. In any event, some nodal points are to be found in almost every image, and in certain cases they may be the dominant feature.

5. Landmarks. Landmarks are another type of point-reference, bur in this case the observer does not enter within them, they are external. They are usually a rather simply defined physical object: building, sign, store, or mountain. Their use involves the singling out of one element from a host of possibilities. Some landmarks are distant ones, typically seen from many angles and distances, over the tops of smaller elements, and used as radial references. They may be within the city or at such a distance that for all practical purposes they symbolize a constant direction. Such are isolated rowers, golden domes, great hills. Even a mobile point, like the sun, whose motion is sufficiently slow and regular, may be employed. Other landmarks are primarily local, being visible only in restricted localities and from certain approaches. These are the innumerable signs, storefronts, trees, doorknobs, and other urban derail, which fill in the image of most

observers. They are frequently used clues of identity and even of structure, and seem to be increasingly relied upon as a journey becomes more and more familiar.

The image of a given physical reality may occasionally shift its type with different circumstances of viewing. Thus an expressway may be a path for the driver, and edge for the pedestrian. Or a central area may be a district when a city is organized on a medium scale, and a node when the entire metropolitan area is considered. But the categories seem to have stability for a given observer when he is operating at a given level.

None of the element types isolated above exist in isolation in the real case. Districts are structured with nodes, defined by edges, penetrated by paths, and sprinkled with landmarks. Elements regularly overlap and pierce one another. If this analysis begins with the differentiation of the data into categories, it must end with their reintegration into the whole image. Our studies have furnished much information about the visual character of the element types. This will be discussed below. Only to a lesser extent, unfortunately, did the work make revelations about the interrelations between elements, or about image levels, image qualities, or the development of the image. These latter topics will be treated at the end of this chapter."

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A total set of anchorpoints then is a combination of those selected in common with others as part of a general pattern of recognition of critical things in an environment (i.e., the common cues that identify cities as being distinct one from another), together with the principal idiosyncratic sets of points at are relevant to any single individual's activity patterns. As interactions occur along the paths between the primary nodes, there is a spillover or spread effect and the development of the concepts of neighborhood, community, region, and so on. Neighborhoods surrounding the primary node sets become known first, and continued interactions along developing node-path networks strengthen the image of segments of the environment for each individual at the same time as they formalize the content and order of the basic common knowledge structure."

1.3. Definitions of Terms.

To operationalize the notion of coherence as a criterion for assessing sketch maps, this study proposes a rubric for evaluating sketch maps (Table 3.2. in Section 3) using the terms defined in this section: *declarative*, *procedural*, *hierarchical*, *topological*, *configurational*, *projective*, and *relational*. However, for some of these terms, theoretical convergences and divergences on the nature of spatial knowledge have resulted in varying definitions (see section 3 for detail): for instance, *relational* knowledge has been used interchangeably with *configurational* knowledge to qualitatively characterize the concept of *proximity* and *sequence* as a more advanced component of spatial knowledge than *declarative* and *procedural* knowledge (Golledge and Stimson, 1997, p163). Furthermore, the concept of *proximity* and *sequence* is thought to allow for the development of various knowledge structures that may be considered hierarchical. Finally, it is also unclear as to whether *relational* is considered synonymous, or similar, to other qualitative descriptors for cognitive maps including *hierarchical*, *topological*, and *projective*. In order to reconcile these varying ways of deploying these terms, this study proposes to reframe *relational* from a possible equivalent of other specific terms to an all-encompassing term meaning "characterized by relations" with relation as an antonym of component. This perspective forms the basis of the proposed sketch map evaluation rubric in section 3. The nuances for other definitions are also discussed in section 3 to situate this study's hypotheses (see Section 1.4) within the literature concerning the nature of spatial knowledge. The following definitions provide a brief introduction to the various rules contained within the rubric for scoring sketch maps (Table 3.2. in Section 3)

1.3.1. Declarative

Merriam-Webster Dictionary describes *declarative* as "comprising memory characterized by the conscious recall of facts and events." Golledge and Stimson (1997) use *declarative* to refer to one of the components concerning the nature of spatial knowledge. In this context, *declarative* component "includes knowledge of objects and/or places together with meanings and significances attached to them." Declarative knowledge is about being able to recognize patterns and scenes associated with destinations of significance.

1.3.2. Procedural

Procedural is defined, by Merriam-Webster Dictionary, as "comprising memory or knowledge concerned with how to manipulate symbols, concepts, and rules to accomplish a task or solve a problem." According to Golledge and Stimson (1997), the development of locomotive abilities (such as wayfinding and route learning) requires the development of *object* and *procedure association*. As a component of spatial knowledge, *procedural* alludes to consisting of "*procedural* rules that link bits of the *declarative* structure."

1.3.3. Hierarchical

According to Merriam-Webster Dictionary, hierarchical is defined as consisting of "a *series* of *levels* with different importance." This generic definition of *hierarchical* is similar to the concept of a *sequence* of *proximity* underlying *relational* component, one of the three components of spatial knowledge put forth by Golledge and Stimson (1997, p163). *Hierarchical* is thus proposed as a more specific term to replace a more generic term *relational* for referring to a *sequence* of *proximity that reflects different levels of importance* as a spatial knowledge structure.

1.3.4. Topological

Merriam-Webster Dictionary defines topological as involving configurational properties (i.e. continuity, connectivity, and proximity) unaltered under elastic deformation by continuous planes such as stretching or twisting. For instance, circle, triangle, and square can be considered topologically identical because they are all formed by a continuous line with conjoined beginning and end points to separate a space into inside and outside areas. Topological component thus introduces aerial concepts of districts, while declarative component implies the point nature of a landmark or node and procedural component refers to the linear nature of a path.

1.3.5. Configurational

According to Merriam-Webster Dictionary, configurational means being characterized by configuration or a distinctive form. The dictionary defines configuration as a *figure* or *pattern* resulting from *relative* arrangement of parts or elements. Configuration has also been equated with gestalt that is more than the sum of its parts. This study thus uses configurational to refer to the wholeness of a figure or pattern as an entity that is more than a collection of declarative, procedural, and topological components and relations.

1.3.6. Projective

Projective is described as “relating to, produced by, or involving geometric projection” by Merriam-Webster Dictionary. This research speculates that projective components and relations may be more abstract than topological and configurational counterparts. Furthermore, it postulates that geometric projection may be either topological or configurational: in the absence of strong forms as perceivable configurations, spatial knowledge about topological properties such as continuity, connectivity, and proximity may be interpolated, extrapolated, and integrated to infer unknown spatial relationships. The existence of a perceived configuration, on the other hand, may also provide a basis for cognitive prognosis beyond known or projected topological properties (such as continuity, connectivity, and proximity).

Sketch Map Evaluation Rubric Two

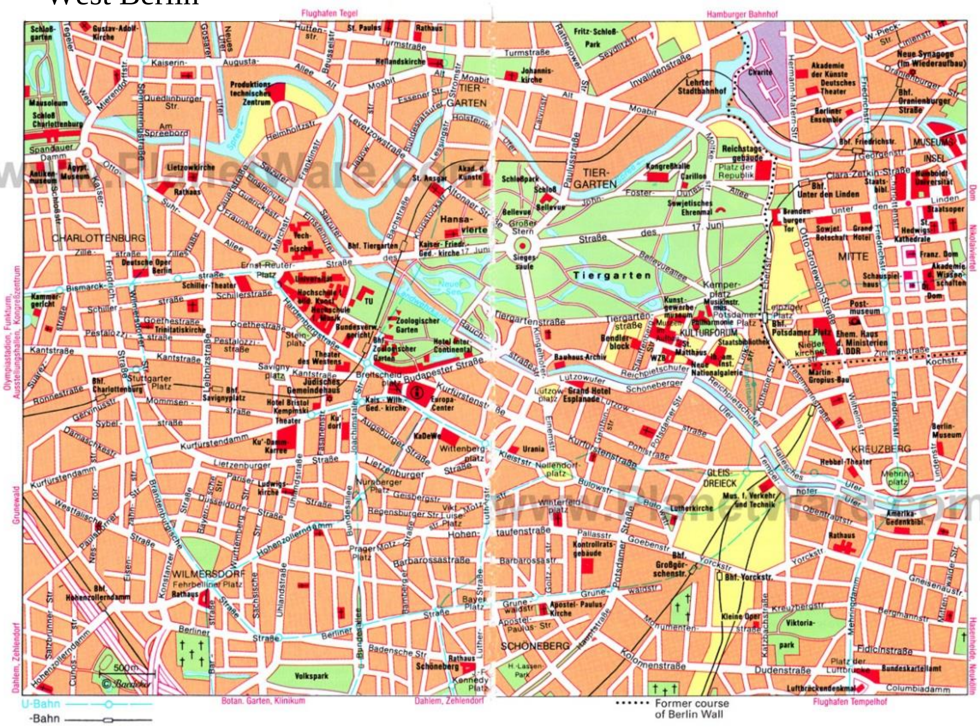
Knowledge Type	**Please select one statement that best describes the sketch map.**
	This sketch map appears to…
Declarative Component	1. Show an impressionist sketch of landmark/node characteristics.
Declarative Relations	2. Illustrate randomly distributed landmarks/nodes unconnected by paths.
Procedural Component	3. Display landmarks/nodes as destinations connected by paths yet with little information about pure path intersections or wayside landmarks.
Procedural Relations	4. Exhibit path segments without wayside landmarks but with some pure path intersections that seem to have been drawn from turn-by-turn instructions.
Hierarchical Component	5. Reveal landmarks/nodes in proximity to major paths, landmark, or nodes without enough pure path intersections to enable shortcut-taking.
Hierarchical Relations	5. Reveal landmarks/nodes in proximity to major paths, landmarks, nodes with enough pure path intersections to enable shortcut-taking.
Topological Component	7. Contain districts that can be delineated based on continuous edges or the clustering of landmarks/nodes.
Topological Relations	8. Show a nested hierarchy of multiple districts that can be delineated based on continuous edges or the clustering of landmarks/nodes.
Configurational Component	9. Indicate a distinct form that resembles only a small part of the city center.
Configurational Relations	10. Capture the entire city structure as one single configuration or a collective pattern greater than the sum of multiple distinct forms.
Projective Component	11. Suggest abstract components from known topological or configurational components instead of district-defining edges on the ground.
Projective Relations	12. Infer abstract relationships from known topological or configurational relationships instead of actual physical relationships between districts.

Amsterdam

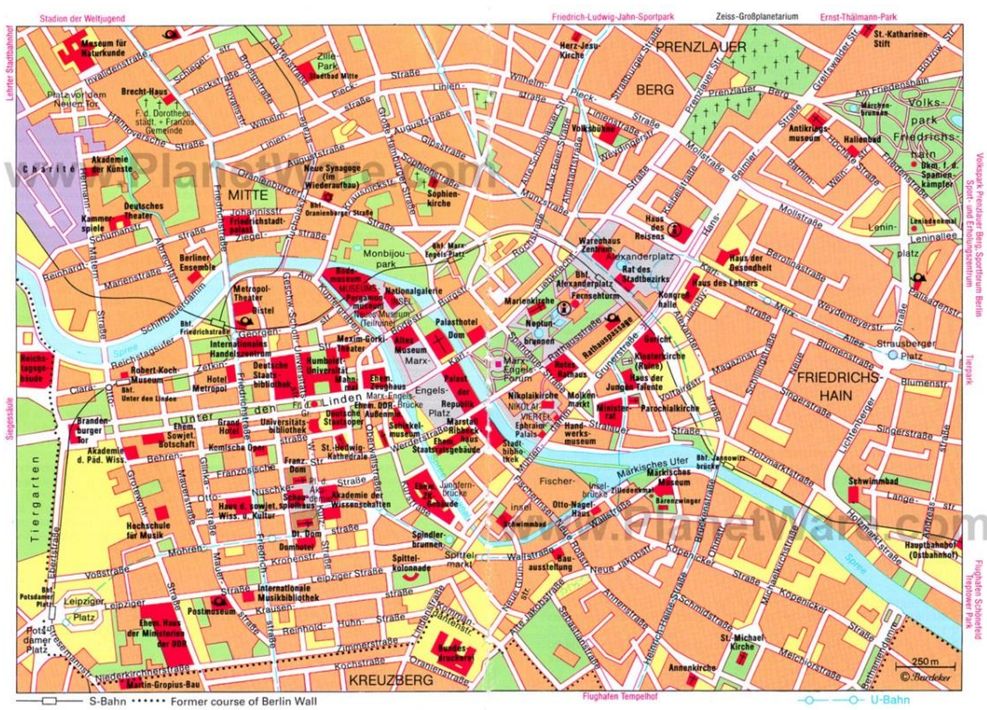
Almere


Marker-
meer
Oost-
vaardersdiep
Noorder-
plassen
Pampus-
haven
ALMERE

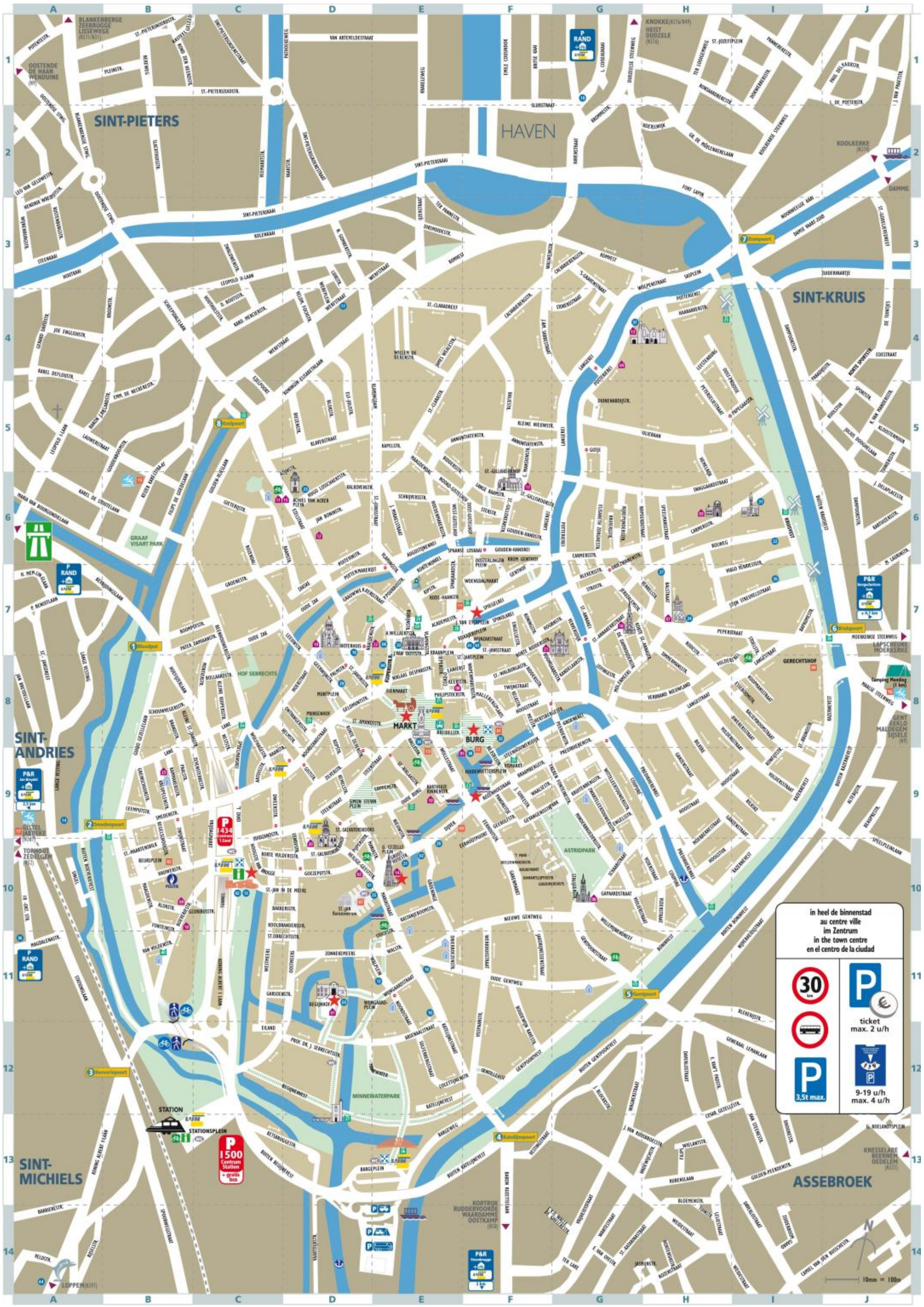
West Berlin



East Berlin



Bruges


A B C D E F G H I J
SINT-PIETERS
HAVEN
SINT-KRUIS
SINT-ANDRIES
MARKT
BURG
SINT-MICHIELS
ASSEBROEK
in heel de binnenstad
au centre ville
im Zentrum
in the town centre
en el centro de la ciudad
30
ticket
max. 2 u/h
3,5t max.
9-19 u/h
max. 4 u/h

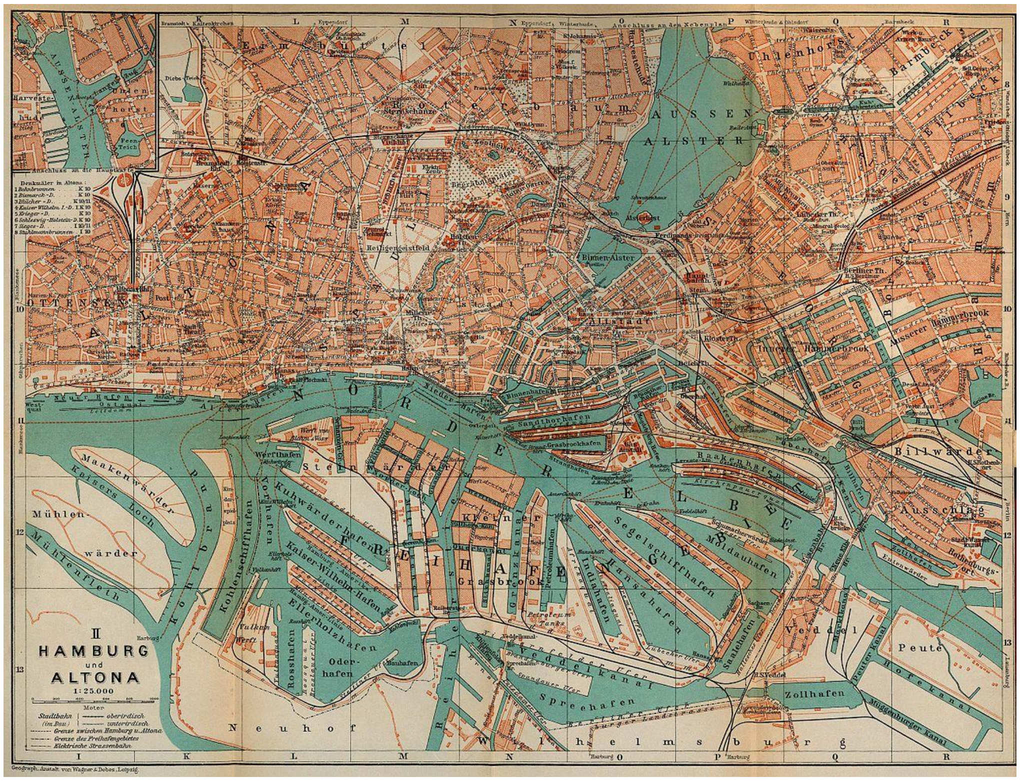
Ghent


GAND, GENT
1 : 23.000
Mètres
1. Athénée D.3.
2. Château des Comtes C.3.
Églises:
3. Ste Anne E.5.
4. des Augustins C.3.
St Bavon (Cathédrale) D.4.
6. Ste Barbe C.5.
7. Ste Elisabeth B.3.
8. St Jacques D.4.
9. St Michel C.4.
10. St Nicolas C.4.
11. St Pierre D.6.
12. St Sauveur D.2.
13. Schreiboom C.6.
14. Abbaye d. St Bavon E.4.
15. Temple protestant D.5.
16. Grande Boucherie C.4.
17. Hospice des Aveugles C.5.
18. Maison des Bateliers C.4.
19. Marché aux Poissons C.4.
20. Palais Episcopal D.4.
21. " de Justice C.5.
22. Poste et Télégraphe C.5.
23. Séminaire Episcopal D.4.
24. Statue d'Artevelde D.3.
25. Théâtre Français C.5.
26. " Flamand C.D.4.
27. Musée d'Archéologie C.3.
Prairies dites de Wondelghem
Faubourg de Bruges
Maison de Force
Hôtel de Ville
Gare du Sud
Parc de la Citadelle
Hôpital Civil
Faubourg de la Colline

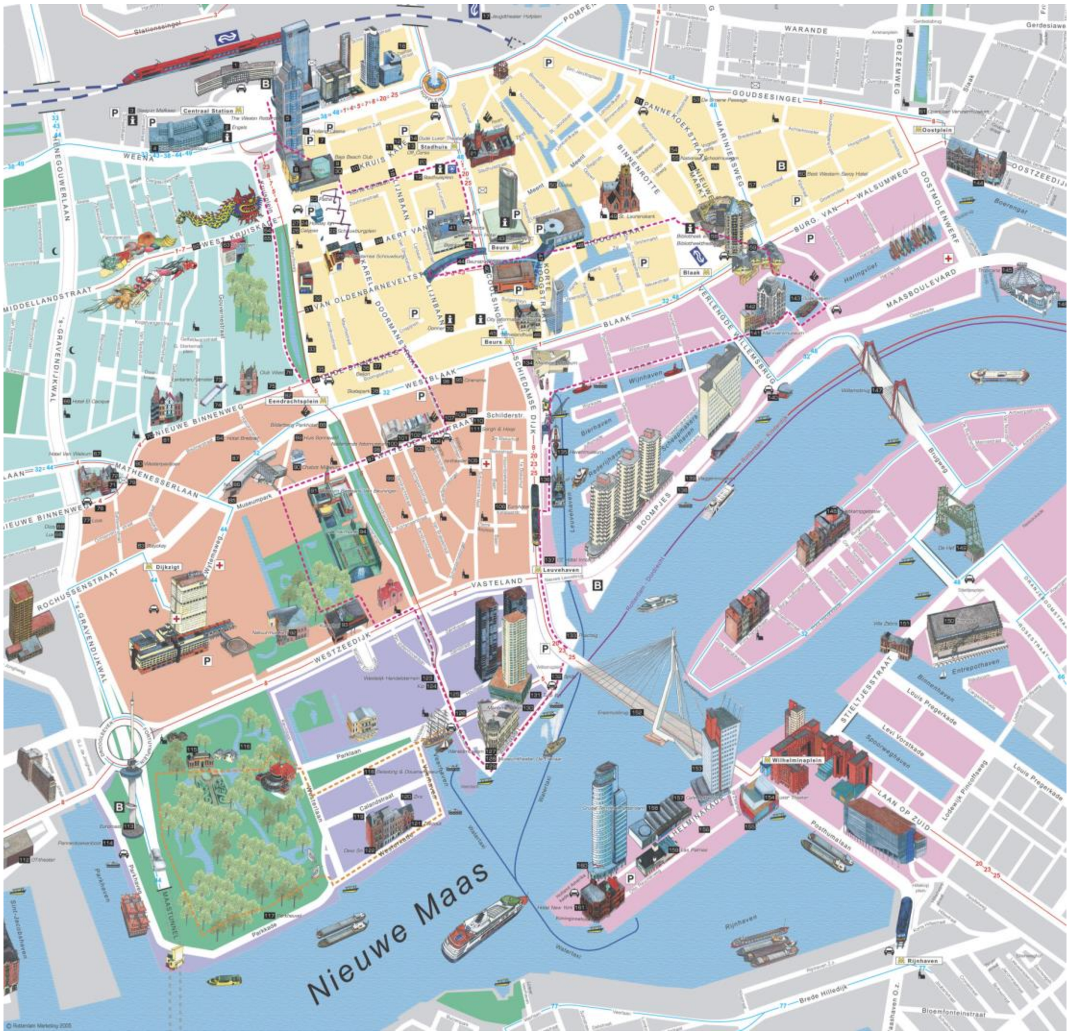
Giethoorn


Heerenveen / Steenwijk / A32
A
B
C
Ontde
GIETHOORN
DWARSGRACHT
GIETHOORN

Hamburg

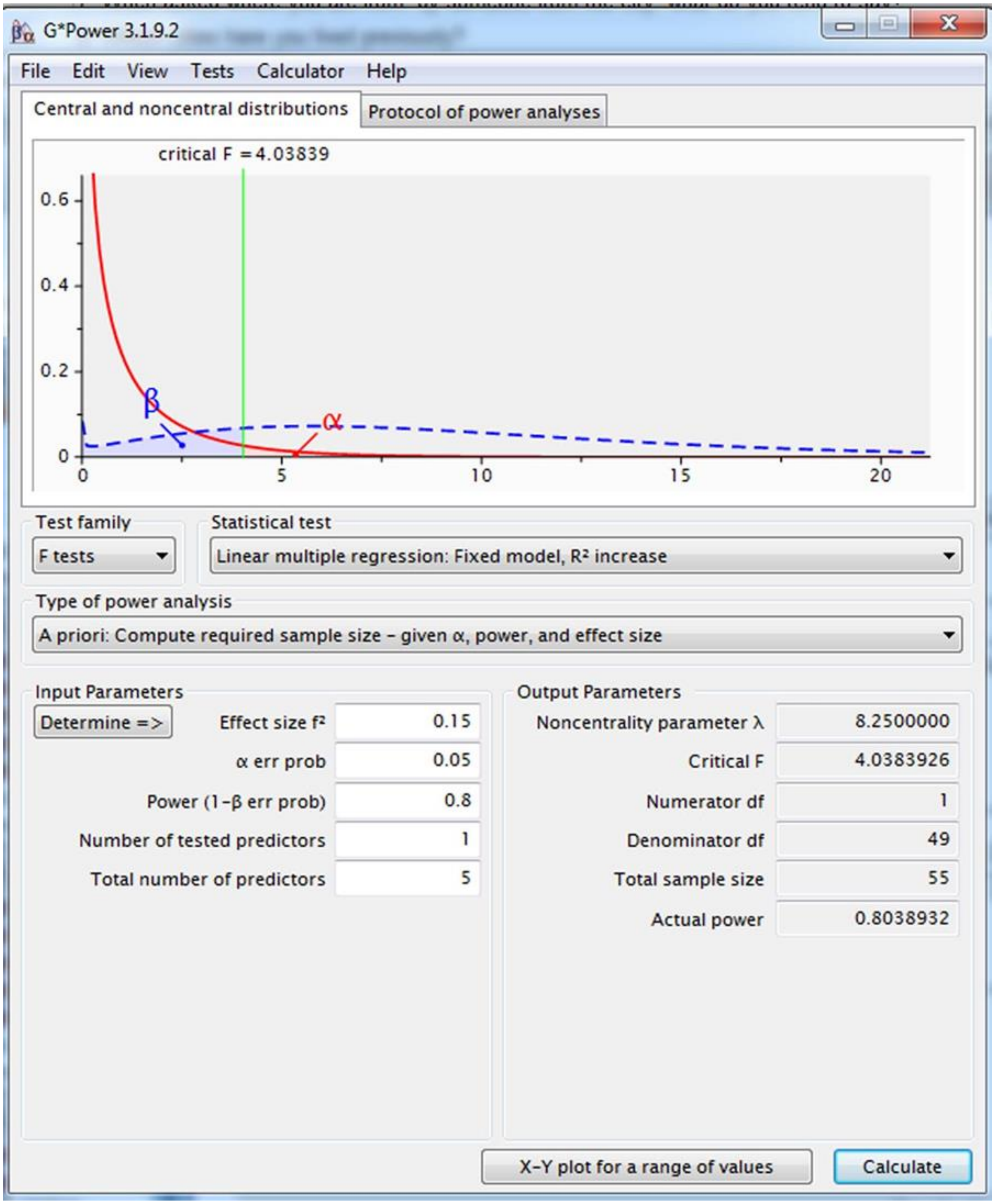

HAMBURG
und
ALTONA
1:25,000
Aussen Alster
Binnen-Alster
Norder Elbe
Freihafen
Altstadt
Ottensen
Uhlenhorst
Veddel
Peute
Zollhafen
Neuhof
Wilhelmsburg
Steinwärder
Kuhwärderhafen
Kaiser-Wilhelm-Hafen
Segelschiffhafen
Oderhafen
Rosshafen
Grasbrook
Billwärder
Moldauhafen
Indiahafen
Hansahafen
Sprehafen
Werfthafen
Kohlenschiffhafen

Rotterdam


Nieuwe Maas
WARANDE
GOUDSESINGEL
Centraal Station
Beurs
Blaak
BLAAK
WESTBLAAK
Eendrachtsplein
Schilderstr
Leuvehaven
BOOMPJES
VASTELAND
WESTZEEDIJK
Dijkzigt
MAASBOULEVARD
Wilhelminaplein
Rijnhaven
Oostplein

APPENDIX C

REGRESSION POWER ANALYSIS RESULTS FROM G*POWER 3.1.9.2.



APPENDIX D

SPSS INTER-RATER RELIABILITY TEST RESULTS

Inter-Rater Reliability of Sketch Map Coherence Measures (N=55)

Variable	Cronbach's Alpha	95% Confidence Interval		F Test with True Value 0				Case N
Raters	ICC Average Measures	Lower Bound	Upper Bound	Value	df1	df2	Sig	Case %
Coherence_1A	.300	-.092	.423	1.429	54	54	.096	55
1&2	.303[b]	-.202	.595	1.429	54	54	.096	91.7
Coherence_1B	.182	-.089	.427	1.439	54	54	.092	55
1&2	.308[b]	-.195	.598	1.439	54	54	.092	91.7
Coherence_1C	.658[a]	.263	.668	2.926	54	54	.000	55
1&2	.659[b]	.416	.801	2.926	54	54	.000	91.7
Coherence_2A	.656[a]	.239	.651	2.909	54	54	.000	55
1&2	.640[b]	.386	.789	2.909	54	54	.000	91.7
Coherence_2B	.606[a]	.166	.605	2.540	54	54	.000	55
1&2	.580[b]	.285	.754	2.540	54	54	.000	91.7
Coherence_2C	.423	.006	.499	1.734	54	54	.023	55
1&2	.426[b]	.013	.665	1.734	54	54	.023	91.7
Coherence_2D	.563	.146	.596	2.289	54	54	.001	55
1&2	.566[b]	.254	.747	2.289	54	54	.001	91.7
Coherence_2E	.545	.120	.571	2.196	54	54	.002	55
1&2	.536[b]	.215	.727	2.196	54	54	.002	91.7
Coherence_2F	.680[a]	.238	.664	3.125	54	54	.000	55
1&2	.649[b]	.384	.798	3.125	54	54	.000	91.7
Coherence_2G	.358	-.044	.441	1.559	54	54	.053	55
1&2	.346[b]	-.091	.612	1.559	54	54	.053	91.7
Coherence_N	.657[a]	.262	.669	2.911	54	54	.000	55
1&2	.659[b]	.415	.802	2.911	54	54	.000	91.7
Coherence_C	.702[a]	.328	.692	3.353	59	59	.000	55
3&4	.696[c]	.494	.818	3.353	59	59	.000	91.7
Coherence_CWA	.682[a]	.270	.664	3.149	59	59	.000	55
3&4	.660[c]	.425	.798	3.149	59	59	.000	91.7
Coherence_CWE	.673[a]	.222	.656	3.058	54	54	.000	55
3&4	.638[c]	.363	.792	3.058	54	54	.000	91.7

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. This value indicates acceptable inter-rater reliability based on .6 as the threshold (McGraw & Wong, 1996).

b. Type A intraclass correlation coefficients using an absolute agreement definition; this estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

APPENDIX E

SPSS INTERNAL CONSISTENCY RELIABILITY TEST RESULTS

Internal Consistency of Sketch Map Coherence Measures – Cronbach's Alpha & Intraclass Correlation Coefficient (ICC)

Variable Names	Cronbach's Alpha	95% Confidence Interval		F Test with True Value 0				Case N
No. of Variables	ICC Average Measures	Lower Bound	Upper Bound	Value	df1	df2	Sig	Case %
Coherence_N&C	.811[a]	.514	.803	5.278	54	54	.000	55
2	.813[c]	.679	.891	5.278	54	54	.000	91.7
Coherence_N&2A	.081	-.043	.089	1.089	54	54	.378	55
2	.019[c]	-.090	.163	1.089	54	54	.378	91.7
Coherence_N&2F	.356	-.050	.457	1.553	54	54	.055	55
2	.359[c]	-.105	.628	1.553	54	54	.055	91.7
Coherence_C&2A	.147	-.042	.106	1.172	54	54	.281	55
2	.036[c]	-.087	.192	1.172	54	54	.281	91.7
Coherence_C&2F	.470	.049	.530	1.888	54	54	.011	55
2	.472[c]	.094	.693	1.888	54	54	.011	91.7
Coherence_2A/2F	.411	-.051	.218	1.698	54	54	.027	55
2	.111[c]	-.108	.358	1.698	54	54	.027	91.7
Coherence_N/C/2A	.188	-.021	.074	1.231	54	108	.180	55
3	.048[c]	-.064	.194	1.231	54	108	.180	91.7
Coherence_N/C/2F	.656	.225	.556	2.906	54	108	.000	55
3	.659[c]	.465	.790	2.906	54	108	.000	91.7
Coherence_N/C/2A/2F	.388	-.009	.096	1.634	54	162	.010	55
4	.117[c]	-.038	.299	1.634	54	162	.010	91.7

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. This value indicates acceptable inter-rater reliability based on .6 as the threshold (McGraw & Wong, 1996).

b. Type A intraclass correlation coefficients using an absolute agreement definition; this estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

APPENDIX F

SPSS REGRESSION ANALYSIS RESULTS AND RESIDUAL PLOTS

```
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  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
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  /DEPENDENT Coherence_2A
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Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.298[a]	.089	.072	3.10991

a. Predictors: (Constant), Visitor or Resident

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.043	1	50.043	5.174	.027[b]
	Residual	512.593	53	9.672		
	Total	562.636	54			

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors: (Constant), Visitor or Resident

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.610	1.319		2.737	.008
	Visitor or Resident	1.908	.839	.298	2.275	.027

a. Dependent Variable: Average 12-Stage Coherence (12C)

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT Coherence_2A
 /METHOD=ENTER TR
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 /METHOD=ENTER A1_R
 /METHOD=ENTER B1_M.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.298[a]	.089	.072	3.10991
2	.371[b]	.138	.104	3.05484
3	.450[c]	.202	.155	2.96648
4	.542[d]	.294	.238	2.81862

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Canal Mappability

c. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.043	1	50.043	5.174	.027[b]
	Residual	512.593	53	9.672		
	Total	562.636	54			
2	Regression	77.371	2	38.686	4.145	.021[c]
	Residual	485.265	52	9.332		
	Total	562.636	54			
3	Regression	113.837	3	37.946	4.312	.009[d]
	Residual	448.799	51	8.800		
	Total	562.636	54			
4	Regression	165.406	4	41.352	5.205	.001[e]
	Residual	397.230	50	7.945		
	Total	562.636	54			

a. Dependent Variable: Average 12-Stage Coherence (12C)
b. Predictors: (Constant), Visitor or Resident
c. Predictors: (Constant), Visitor or Resident, Canal Mappability
d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability
e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.226[b]	1.711	.093	.231	.950
	River Mappability	.200[b]	1.537	.130	.208	.993
	Water Landmark Identifiability	.280[b]	2.172	.034	.288	.963
2	River Mappability	.262[c]	2.036	.047	.274	.943
	Water Landmark Identifiability	.251[c]	1.939	.058	.262	.939
3	Water Landmark Identifiability	.319[d]	2.548	.014	.339	.899

a. Dependent Variable: Average 12-Stage Coherence (12C)
b. Predictors in the Model: (Constant), Visitor or Resident
c. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability
d. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.610	1.319		2.737	.008
	Visitor or Resident	1.908	.839	.298	2.275	.027
2	(Constant)	3.493	1.297		2.693	.010
	Visitor or Resident	1.584	.845	.248	1.873	.067
	Canal Mappability	.268	.157	.226	1.711	.093
3	(Constant)	3.284	1.264		2.598	.012
	Visitor or Resident	1.356	.829	.212	1.637	.108
	Canal Mappability	.339	.156	.286	2.172	.035
	River Mappability	.390	.192	.262	2.036	.047
4	(Constant)	3.165	1.202		2.633	.011
	Visitor or Resident	.980	.801	.153	1.223	.227
	Canal Mappability	.296	.149	.250	1.986	.053
	River Mappability	.488	.186	.328	2.624	.011
	Water Landmark Identifiability	.348	.137	.319	2.548	.014

a. Dependent Variable: Average 12-Stage Coherence (12C)

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  /STATISTICS COEFF OUTS R ANOVA
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  /NOORIGIN
  /DEPENDENT Coherence_2A
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  /METHOD=ENTER A1_C
  /METHOD=ENTER A1_R
  /METHOD=ENTER H5_N.
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Length of Exposure Normalized[b]	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.271[a]	.073	.054	3.05954
2	.331[b]	.109	.072	3.03059
3	.394[c]	.155	.101	2.98284
4	.394[d]	.155	.082	3.01491

a. Predictors: (Constant), Visitor or Resident
b. Predictors: (Constant), Visitor or Resident, Canal Mappability
c. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability
d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Length of Exposure Normalized

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.302	1	36.302	3.878	.055[b]
	Residual	458.678	49	9.361		
	Total	494.980	50			
2	Regression	54.125	2	27.062	2.947	.062[c]
	Residual	440.856	48	9.184		
	Total	494.980	50			
3	Regression	76.805	3	25.602	2.877	.046[d]
	Residual	418.175	47	8.897		
	Total	494.980	50			
4	Regression	76.855	4	19.214	2.114	.094[e]
	Residual	418.125	46	9.090		
	Total	494.980	50			

a. Dependent Variable: Average 12-Stage Coherence (12C)
b. Predictors: (Constant), Visitor or Resident
c. Predictors: (Constant), Visitor or Resident, Canal Mappability
d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability
e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Length of Exposure Normalized

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.005	1.347		2.973	.005
	Visitor or Resident	1.688	.857	.271	1.969	.055
2	(Constant)	3.842	1.339		2.869	.006
	Visitor or Resident	1.461	.864	.234	1.690	.097
	Canal Mappability	.220	.158	.193	1.393	.170
3	(Constant)	3.585	1.328		2.700	.010
	Visitor or Resident	1.316	.856	.211	1.538	.131
	Canal Mappability	.288	.161	.253	1.788	.080
	River Mappability	.318	.199	.222	1.597	.117
4	(Constant)	3.631	1.477		2.458	.018
	Visitor or Resident	1.265	1.099	.203	1.152	.255
	Canal Mappability	.290	.164	.255	1.764	.084
	River Mappability	.320	.203	.224	1.577	.122
	Length of Exposure Normalized	.027	.368	.013	.074	.941

a. Dependent Variable: Average 12-Stage Coherence (12C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.193[b]	1.393	.170	.197	.965
	River Mappability	.156[b]	1.138	.261	.162	.997
	Length of Exposure Normalized	-.044[b]	-.252	.802	-.036	.634
2	River Mappability	.222[c]	1.597	.117	.227	.927
	Length of Exposure Normalized	-.020[c]	-.113	.911	-.016	.627
3	Length of Exposure Normalized	.013[d]	.074	.941	.011	.618

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability

d. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability

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  /STATISTICS COEFF OUTS R ANOVA
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  /NOORIGIN
  /DEPENDENT Coherence_2A
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  /METHOD=ENTER A1_C
  /METHOD=ENTER A1_R
  /METHOD=ENTER B1_M
  /METHOD=ENTER D1_R.
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Length of Exposure Normalized[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)
b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.125[a]	.016	-.006	3.15670
2	.292[b]	.085	.045	3.07655
3	.374[c]	.140	.081	3.01755
4	.480[d]	.230	.158	2.88766
5	.551[e]	.304	.221	2.77878

a. Predictors: (Constant), Length of Exposure Normalized
b. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability
c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability
d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability
e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.289	1	7.289	.731	.397[b]
	Residual	458.378	46	9.965		
	Total	465.667	47			
2	Regression	39.735	2	19.868	2.099	.134[c]
	Residual	425.931	45	9.465		
	Total	465.667	47			
3	Regression	65.021	3	21.674	2.380	.082[d]
	Residual	400.646	44	9.106		
	Total	465.667	47			
4	Regression	107.107	4	26.777	3.211	.022[e]
	Residual	358.559	43	8.339		
	Total	465.667	47			
5	Regression	141.358	5	28.272	3.661	.008[f]
	Residual	324.308	42	7.722		
	Total	465.667	47			

a. Dependent Variable: Average Coherence 2A
b. Predictors: (Constant), Length of Exposure Normalized
c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability
d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability
e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability
f. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	6.189	.528		11.721	.000
	Length of Exposure Normalized	.261	.305	.125	.855	.397
2	(Constant)	5.531	.625		8.844	.000
	Length of Exposure Normalized	.236	.297	.113	.793	.432
	Canal Mappability	.294	.159	.264	1.851	.071
3	(Constant)	5.034	.682		7.382	.000
	Length of Exposure Normalized	.259	.292	.124	.888	.379
	Canal Mappability	.356	.160	.320	2.222	.032
	River Mappability	.341	.204	.240	1.666	.103
4	(Constant)	4.489	.696		6.449	.000
	Length of Exposure Normalized	.144	.284	.069	.506	.616
	Canal Mappability	.307	.155	.276	1.984	.054
	River Mappability	.419	.199	.295	2.110	.041
	Water Landmark Identifiability	.327	.146	.316	2.247	.030
5	(Constant)	6.837	1.301		5.257	.000
	Length of Exposure Normalized	.078	.275	.037	.283	.779
	Canal Mappability	.316	.149	.284	2.121	.040
	River Mappability	.411	.191	.289	2.147	.038
	Water Landmark Identifiability	.365	.141	.353	2.583	.013
	Aquaphilia Sensitivity Baseline	-1.166	.554	-.275	-2.106	.041

a. Dependent Variable: Average 12-Stage Coherence (12C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Canal Mappability	.264[b]	1.851	.071	.266	.998
	River Mappability	.166[b]	1.137	.262	.167	.997
	Water Landmark Identifiability	.304[b]	2.118	.040	.301	.963
	Aquaphilia Sensitivity Baseline	-.226[b]	-1.563	.125	-.227	.992
2	River Mappability	.240[c]	1.666	.103	.244	.944
	Water Landmark Identifiability	.264[c]	1.834	.073	.267	.931
	Aquaphilia Sensitivity Baseline	-.242[c]	-1.727	.091	-.252	.989
3	Water Landmark Identifiability	.316[d]	2.247	.030	.324	.903
	Aquaphilia Sensitivity Baseline	-.232[d]	-1.686	.099	-.249	.987
4	Aquaphilia Sensitivity Baseline	-.275[e]	-2.106	.041	-.309	.971

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors in the Model: (Constant), Length of Exposure Normalized

c. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability

d. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

e. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

```
REGRESSION
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 /STATISTICS COEFF OUTS R ANOVA
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 /NOORIGIN
 /DEPENDENT Coherence_2B
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 /METHOD=ENTER A1_C
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Length of Exposure Normalized[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.148[a]	.022	.001	2.09965
2	.321[b]	.103	.063	2.03297
3	.377[c]	.142	.083	2.01063
4	.502[d]	.252	.182	1.89940
5	.637[e]	.405	.335	1.71318

a. Predictors: (Constant), Length of Exposure Normalized

b. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability

c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.521	1	4.521	1.026	.317[b]
	Residual	202.792	46	4.409		
	Total	207.312	47			
2	Regression	21.330	2	10.665	2.580	.087[c]
	Residual	185.983	45	4.133		
	Total	207.312	47			
3	Regression	29.437	3	9.812	2.427	.078[d]
	Residual	177.876	44	4.043		
	Total	207.312	47			
4	Regression	52.180	4	13.045	3.616	.013[e]
	Residual	155.133	43	3.608		
	Total	207.312	47			
5	Regression	84.043	5	16.809	5.727	.000[f]
	Residual	123.269	42	2.935		
	Total	207.312	47			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Length of Exposure Normalized

c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability

d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

f. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	5.133	.351		14.616	.000
	Length of Exposure Normalized	.205	.203	.148	1.013	.317
2	(Constant)	4.659	.413		11.275	.000
	Length of Exposure Normalized	.187	.196	.135	.954	.345
	Canal Mappability	.212	.105	.285	2.017	.050
3	(Constant)	4.378	.454		9.636	.000
	Length of Exposure Normalized	.201	.195	.144	1.031	.308
	Canal Mappability	.246	.107	.332	2.311	.026
	River Mappability	.193	.136	.204	1.416	.164
4	(Constant)	3.978	.458		8.687	.000
	Length of Exposure Normalized	.116	.187	.083	.619	.539
	Canal Mappability	.211	.102	.284	2.070	.044
	River Mappability	.251	.131	.265	1.918	.062
	Water Landmark Identifiability	.241	.096	.349	2.511	.016
5	(Constant)	6.242	.802		7.784	.000
	Length of Exposure Normalized	.052	.170	.038	.307	.760
	Canal Mappability	.219	.092	.296	2.390	.021
	River Mappability	.242	.118	.256	2.055	.046
	Water Landmark Identifiability	.277	.087	.401	3.179	.003
	Aquaphilia Sensitivity Baseline	-1.125	.341	-.398	-3.295	.002

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Canal Mappability	.285[b]	2.017	.050	.288	.998
	River Mappability	.127[b]	.866	.391	.128	.997
	Water Landmark Identifiability	.345[b]	2.441	.019	.342	.963
	Aquaphilia Sensitivity Baseline	-.339[b]	-2.440	.019	-.342	.992
2	River Mappability	.204[c]	1.416	.164	.209	.944
	Water Landmark Identifiability	.302[c]	2.143	.038	.307	.931
	Aquaphilia Sensitivity Baseline	-.357[c]	-2.685	.010	-.375	.989
3	Water Landmark Identifiability	.349[d]	2.511	.016	.358	.903
	Aquaphilia Sensitivity Baseline	-.349[d]	-2.649	.011	-.375	.987
4	Aquaphilia Sensitivity Baseline	-.398[e]	-3.295	.002	-.453	.971

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Length of Exposure Normalized

c. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability

d. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

e. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

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REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
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  /METHOD=ENTER A1_R
  /METHOD=ENTER B1_M
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.298[a]	.089	.070	2.05664
2	.389[b]	.151	.116	2.00592
3	.432[c]	.187	.135	1.98386
4	.543[d]	.295	.234	1.86682
5	.646[e]	.417	.353	1.71635

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Canal Mappability

c. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	34.343	2	17.171	4.268	.020[c]
	Residual	193.138	48	4.024		
	Total	227.480	50			
3	Regression	42.502	3	14.167	3.600	.020[d]
	Residual	184.978	47	3.936		
	Total	227.480	50			
4	Regression	67.169	4	16.792	4.818	.002[e]
	Residual	160.311	46	3.485		
	Total	227.480	50			
5	Regression	94.917	5	18.983	6.444	.000[f]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

f. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	3.278	.874		3.749	.000
	Visitor or Resident	1.001	.580	.237	1.727	.091
	Canal Mappability	.197	.105	.257	1.873	.067
3	(Constant)	3.134	.871		3.599	.001
	Visitor or Resident	.926	.576	.219	1.608	.114
	Canal Mappability	.232	.107	.302	2.173	.035
	River Mappability	.192	.133	.195	1.440	.157
4	(Constant)	3.016	.820		3.676	.001
	Visitor or Resident	.693	.549	.164	1.263	.213
	Canal Mappability	.198	.101	.258	1.950	.057
	River Mappability	.251	.127	.254	1.969	.055
	Water Landmark Identifiability	.246	.092	.345	2.660	.011
5	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Water Landmark Identifiability	.269	.085	.377	3.149	.003
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
2	River Mappability	.195[c]	1.440	.157	.206	.947
	Water Landmark Identifiability	.301[c]	2.285	.027	.316	.938
	Aquaphilia Sensitivity Baseline	-.332[c]	-2.625	.012	-.358	.987
3	Water Landmark Identifiability	.345[d]	2.660	.011	.365	.910
	Aquaphilia Sensitivity Baseline	-.322[d]	-2.569	.014	-.354	.984
4	Aquaphilia Sensitivity Baseline	-.353[e]	-3.069	.004	-.416	.976

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability

d. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

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REGRESSION
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  /DEPENDENT Coherence_2B
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  /METHOD=ENTER B1_M
  /METHOD=ENTER D1_R.
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Length of Exposure Normalized[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

				Std. Error of the Estimate	Change Statistics				
Model	R	R Square	Adjusted R Square		R Square Change	F Change	df1	df2	Sig. F Change
1	.148[a]	.022	.001	2.09965	.022	1.026	1	46	.317
2	.321[b]	.103	.063	2.03297	.081	4.067	1	45	.050
3	.377[c]	.142	.083	2.01063	.039	2.005	1	44	.164
4	.502[d]	.252	.182	1.89940	.110	6.304	1	43	.016
5	.637[e]	.405	.335	1.71318	.154	10.856	1	42	.002

a. Predictors: (Constant), Length of Exposure Normalized

b. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability

c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.521	1	4.521	1.026	.317[b]
	Residual	202.792	46	4.409		
	Total	207.312	47			
2	Regression	21.330	2	10.665	2.580	.087[c]
	Residual	185.983	45	4.133		
	Total	207.312	47			
3	Regression	29.437	3	9.812	2.427	.078[d]
	Residual	177.876	44	4.043		
	Total	207.312	47			
4	Regression	52.180	4	13.045	3.616	.013[e]
	Residual	155.133	43	3.608		
	Total	207.312	47			
5	Regression	84.043	5	16.809	5.727	.000[f]
	Residual	123.269	42	2.935		
	Total	207.312	47			

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors: (Constant), Length of Exposure Normalized
c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability
d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability
e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability
f. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	5.133	.351		14.616	.000
	Length of Exposure Normalized	.205	.203	.148	1.013	.317
2	(Constant)	4.659	.413		11.275	.000
	Length of Exposure Normalized	.187	.196	.135	.954	.345
	Canal Mappability	.212	.105	.285	2.017	.050
3	(Constant)	4.378	.454		9.636	.000
	Length of Exposure Normalized	.201	.195	.144	1.031	.308
	Canal Mappability	.246	.107	.332	2.311	.026
	River Mappability	.193	.136	.204	1.416	.164
4	(Constant)	3.978	.458		8.687	.000
	Length of Exposure Normalized	.116	.187	.083	.619	.539
	Canal Mappability	.211	.102	.284	2.070	.044
	River Mappability	.251	.131	.265	1.918	.062
	Water Landmark Identifiability	.241	.096	.349	2.511	.016
5	(Constant)	6.242	.802		7.784	.000
	Length of Exposure Normalized	.052	.170	.038	.307	.760
	Canal Mappability	.219	.092	.296	2.390	.021
	River Mappability	.242	.118	.256	2.055	.046
	Water Landmark Identifiability	.277	.087	.401	3.179	.003
	Aquaphilia Sensitivity Baseline	-1.125	.341	-.398	-3.295	.002

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.285[b]	2.017	.050	.288	.998
	River Mappability	.127[b]	.866	.391	.128	.997
	Water Landmark Identifiability	.345[b]	2.441	.019	.342	.963
	Aquaphilia Sensitivity Baseline	-.339[b]	-2.440	.019	-.342	.992
2	River Mappability	.204[c]	1.416	.164	.209	.944
	Water Landmark Identifiability	.302[c]	2.143	.038	.307	.931
	Aquaphilia Sensitivity Baseline	-.357[c]	-2.685	.010	-.375	.989
3	Water Landmark Identifiability	.349[d]	2.511	.016	.358	.903
	Aquaphilia Sensitivity Baseline	-.349[d]	-2.649	.011	-.375	.987
4	Aquaphilia Sensitivity Baseline	-.398[e]	-3.295	.002	-.453	.971

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors in the Model: (Constant), Length of Exposure Normalized
c. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability
d. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability
e. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

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REGRESSION
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 /DEPENDENT Coherence_2B
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 /METHOD=ENTER B1_M
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.389[b]	.151	.116	2.00592	.062	3.509	1	48	.067
3	.432[c]	.187	.135	1.98386	.036	2.073	1	47	.157
4	.543[d]	.295	.234	1.86682	.108	7.078	1	46	.011
5	.646[e]	.417	.353	1.71635	.122	9.419	1	45	.004

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Canal Mappability

c. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	34.343	2	17.171	4.268	.020[c]
	Residual	193.138	48	4.024		
	Total	227.480	50			
3	Regression	42.502	3	14.167	3.600	.020[d]
	Residual	184.978	47	3.936		
	Total	227.480	50			
4	Regression	67.169	4	16.792	4.818	.002[e]
	Residual	160.311	46	3.485		
	Total	227.480	50			
5	Regression	94.917	5	18.983	6.444	.000[f]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

f. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	3.278	.874		3.749	.000
	Visitor or Resident	1.001	.580	.237	1.727	.091
	Canal Mappability	.197	.105	.257	1.873	.067
3	(Constant)	3.134	.871		3.599	.001
	Visitor or Resident	.926	.576	.219	1.608	.114
	Canal Mappability	.232	.107	.302	2.173	.035
	River Mappability	.192	.133	.195	1.440	.157
4	(Constant)	3.016	.820		3.676	.001
	Visitor or Resident	.693	.549	.164	1.263	.213
	Canal Mappability	.198	.101	.258	1.950	.057
	River Mappability	.251	.127	.254	1.969	.055
	Water Landmark Identifiability	.246	.092	.345	2.660	.011
5	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Water Landmark Identifiability	.269	.085	.377	3.149	.003
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
2	River Mappability	.195[c]	1.440	.157	.206	.947
	Water Landmark Identifiability	.301[c]	2.285	.027	.316	.938
	Aquaphilia Sensitivity Baseline	-.332[c]	-2.625	.012	-.358	.987
3	Water Landmark Identifiability	.345[d]	2.660	.011	.365	.910
	Aquaphilia Sensitivity Baseline	-.322[d]	-2.569	.014	-.354	.984
4	Aquaphilia Sensitivity Baseline	-.353[e]	-3.069	.004	-.416	.976

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability

d. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Length of Exposure Normalized[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.050[a]	.002	-.019	.77195	.002	.114	1	46	.738
2	.444[b]	.197	.161	.70031	.194	10.892	1	45	.002
3	.444[c]	.197	.143	.70800	.000	.027	1	44	.869
4	.445[d]	.198	.124	.71570	.001	.058	1	43	.811
5	.534[e]	.285	.200	.68403	.086	5.075	1	42	.030

a. Predictors: (Constant), Length of Exposure Normalized

b. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability

c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.068	1	.068	.114	.738[b]
	Residual	27.412	46	.596		
	Total	27.479	47			
2	Regression	5.410	2	2.705	5.515	.007[c]
	Residual	22.070	45	.490		
	Total	27.479	47			
3	Regression	5.423	3	1.808	3.606	.021[d]
	Residual	22.056	44	.501		
	Total	27.479	47			
4	Regression	5.453	4	1.363	2.661	.045[e]
	Residual	22.026	43	.512		
	Total	27.479	47			
5	Regression	7.828	5	1.566	3.346	.012[f]
	Residual	19.652	42	.468		
	Total	27.479	47			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors: (Constant), Length of Exposure Normalized

c. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability

d. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

e. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

f. Predictors: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.918	.129		14.854	.000
	Length of Exposure Normalized	-.025	.075	-.050	-.337	.738
2	(Constant)	1.651	.142		11.597	.000
	Length of Exposure Normalized	-.035	.068	-.070	-.520	.606
	Canal Mappability	.119	.036	.441	3.300	.002
3	(Constant)	1.662	.160		10.390	.000
	Length of Exposure Normalized	-.036	.069	-.071	-.522	.604
	Canal Mappability	.118	.038	.436	3.138	.003
	River Mappability	-.008	.048	-.023	-.165	.869
4	(Constant)	1.648	.173		9.551	.000
	Length of Exposure Normalized	-.039	.070	-.077	-.551	.584
	Canal Mappability	.117	.038	.431	3.040	.004
	River Mappability	-.006	.049	-.017	-.119	.906
	Water Landmark Identifiability	.009	.036	.035	.241	.811
5	(Constant)	2.266	.320		7.078	.000
	Length of Exposure Normalized	-.056	.068	-.111	-.829	.412
	Canal Mappability	.119	.037	.440	3.244	.002
	River Mappability	-.008	.047	-.024	-.172	.864
	Water Landmark Identifiability	.019	.035	.074	.536	.595
	Aquaphilia Sensitivity Baseline	-.307	.136	-.298	-2.253	.030

a. Dependent Variable: Water-Based Egocentric Coherence

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.441[b]	3.300	.002	.441	.998
	River Mappability	-.124[b]	-.837	.407	-.124	.997
	Water Landmark Identifiability	.118[b]	.784	.437	.116	.963
	Aquaphilia Sensitivity Baseline	-.261[b]	-1.807	.077	-.260	.992
2	River Mappability	-.023[c]	-.165	.869	-.025	.944
	Water Landmark Identifiability	.038[c]	.269	.789	.041	.931
	Aquaphilia Sensitivity Baseline	-.288[c]	-2.235	.031	-.319	.989
3	Water Landmark Identifiability	.035[d]	.241	.811	.037	.903
	Aquaphilia Sensitivity Baseline	-.289[d]	-2.221	.032	-.321	.987
4	Aquaphilia Sensitivity Baseline	-.298[e]	-2.253	.030	-.328	.971

a. Dependent Variable: Water-Based Egocentric Coherence

b. Predictors in the Model: (Constant), Length of Exposure Normalized

c. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability

d. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability

e. Predictors in the Model: (Constant), Length of Exposure Normalized, Canal Mappability, River Mappability, Water Landmark Identifiability

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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Water Landmark Identifiability[b]	.	Enter
3	Canal Mappability[b]	.	Enter
4	River Mappability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. All requested variables entered.

Model Summary

				Std. Error of the Estimate	Change Statistics				
Model	R	R Square	Adjusted R Square		R Square Change	F Change	df1	df2	Sig. F Change
1	.102[a]	.010	-.010	.76720	.010	.519	1	49	.475
2	.189[b]	.036	-.004	.76517	.025	1.260	1	48	.267
3	.504[c]	.254	.207	.68011	.218	13.757	1	47	.001
4	.506[d]	.256	.191	.68681	.001	.088	1	46	.769
5	.611[e]	.374	.304	.63694	.118	8.486	1	45	.006

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability

c. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

e. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.306	1	.306	.519	.475[b]
	Residual	28.841	49	.589		
	Total	29.147	50			
2	Regression	1.044	2	.522	.891	.417[c]
	Residual	28.103	48	.585		
	Total	29.147	50			
3	Regression	7.407	3	2.469	5.338	.003[d]
	Residual	21.740	47	.463		
	Total	29.147	50			
4	Regression	7.448	4	1.862	3.947	.008[e]
	Residual	21.699	46	.472		
	Total	29.147	50			
5	Regression	10.891	5	2.178	5.369	.001[f]
	Residual	18.256	45	.406		
	Total	29.147	50			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability

d. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

e. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

f. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.081	.334		6.226	.000
	Visitor or Resident	-.155	.215	-.102	-.721	.475
2	(Constant)	2.067	.334		6.195	.000
	Visitor or Resident	-.200	.218	-.132	-.918	.363
	Water Landmark Identifiability	.041	.037	.162	1.123	.267
3	(Constant)	2.038	.297		6.870	.000
	Visitor or Resident	-.355	.199	-.234	-1.789	.080
	Water Landmark Identifiability	.021	.033	.081	.619	.539
	Canal Mappability	.134	.036	.488	3.709	.001
4	(Constant)	2.027	.302		6.715	.000
	Visitor or Resident	-.362	.202	-.239	-1.793	.079
	Water Landmark Identifiability	.022	.034	.087	.655	.515
	Canal Mappability	.136	.037	.496	3.657	.001
	River Mappability	.014	.047	.039	.296	.769
5	(Constant)	2.846	.397		7.172	.000
	Visitor or Resident	-.427	.189	-.282	-2.265	.028
	Water Landmark Identifiability	.030	.032	.119	.957	.344
	Canal Mappability	.139	.035	.508	4.032	.000
	River Mappability	.009	.044	.025	.201	.842
	Aquaphilia Sensitivity Baseline	-.357	.123	-.348	-2.913	.006

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Water Landmark Identifiability	.162[b]	1.123	.267	.160	.966
	Canal Mappability	.502[b]	3.894	.000	.490	.942
	River Mappability	-.089[b]	-.619	.539	-.089	.999
	Aquaphilia Sensitivity Baseline	-.310[b]	-2.256	.029	-.310	.990
2	Canal Mappability	.488[c]	3.709	.001	.476	.916
	River Mappability	-.058[c]	-.399	.692	-.058	.957
	Aquaphilia Sensitivity Baseline	-.329[c]	-2.414	.020	-.332	.979
3	River Mappability	.039[d]	.296	.769	.044	.918
	Aquaphilia Sensitivity Baseline	-.349[d]	-2.955	.005	-.399	.978
4	Aquaphilia Sensitivity Baseline	-.348[e]	-2.913	.006	-.398	.976

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability

d. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Water Landmark Identifiability[b]	.	Enter
3	Canal Mappability[b]	.	Enter
4	River Mappability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)
b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.234[a]	.055	.035	3.10663	.055	2.827	1	49	.099
2	.380[b]	.145	.109	2.98567	.090	5.051	1	48	.029
3	.426[c]	.182	.129	2.95112	.037	2.131	1	47	.151
4	.509[d]	.259	.195	2.83823	.078	4.813	1	46	.033
5	.567[e]	.321	.246	2.74718	.062	4.100	1	45	.049

a. Predictors: (Constant), Visitor or Resident
b. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability
c. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability
d. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability
e. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.280	1	27.280	2.827	.099[b]
	Residual	472.906	49	9.651		
	Total	500.186	50			
2	Regression	72.302	2	36.151	4.055	.024[c]
	Residual	427.884	48	8.914		
	Total	500.186	50			
3	Regression	90.859	3	30.286	3.478	.023[d]
	Residual	409.327	47	8.709		
	Total	500.186	50			
4	Regression	129.632	4	32.408	4.023	.007[e]
	Residual	370.555	46	8.056		
	Total	500.186	50			
5	Regression	160.572	5	32.114	4.255	.003[f]
	Residual	339.615	45	7.547		
	Total	500.186	50			

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability

d. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

e. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

f. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.090	1.353		3.022	.004
	Visitor or Resident	1.465	.872	.234	1.681	.099
2	(Constant)	3.978	1.302		3.056	.004
	Visitor or Resident	1.111	.852	.177	1.304	.198
	Water Landmark Identifiability	.323	.144	.305	2.247	.029
3	(Constant)	3.929	1.287		3.053	.004
	Visitor or Resident	.847	.862	.135	.983	.331
	Water Landmark Identifiability	.287	.144	.272	1.995	.052
	Canal Mappability	.229	.157	.201	1.460	.151
4	(Constant)	3.593	1.247		2.881	.006
	Visitor or Resident	.635	.834	.101	.762	.450
	Water Landmark Identifiability	.341	.141	.322	2.424	.019
	Canal Mappability	.297	.154	.261	1.928	.060
	River Mappability	.425	.194	.291	2.194	.033
5	(Constant)	6.050	1.712		3.534	.001
	Visitor or Resident	.441	.813	.070	.542	.591
	Water Landmark Identifiability	.365	.137	.345	2.670	.011
	Canal Mappability	.306	.149	.269	2.053	.046
	River Mappability	.410	.188	.280	2.183	.034
	Aquaphilia Sensitivity Baseline	-1.070	.528	-.252	-2.025	.049

a. Dependent Variable: Average 12-Stage Coherence (12C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Water Landmark Identifiability	.305[b]	2.247	.029	.309	.966
	Canal Mappability	.248[b]	1.768	.083	.247	.942
	River Mappability	.168[b]	1.211	.232	.172	.999
	Aquaphilia Sensitivity Baseline	-.221[b]	-1.607	.115	-.226	.990
2	Canal Mappability	.201[c]	1.460	.151	.208	.916
	River Mappability	.239[c]	1.793	.079	.253	.957
	Aquaphilia Sensitivity Baseline	-.255[c]	-1.941	.058	-.272	.979
3	River Mappability	.291[d]	2.194	.033	.308	.918
	Aquaphilia Sensitivity Baseline	-.263[d]	-2.034	.048	-.287	.978
4	Aquaphilia Sensitivity Baseline	-.252[e]	-2.025	.049	-.289	.976

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability

d. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Water Landmark Identifiability[b]	.	Enter
3	Canal Mappability[b]	.	Enter
4	River Mappability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.444[b]	.197	.164	1.95043	.108	6.482	1	48	.014
3	.486[c]	.236	.187	1.92312	.039	2.373	1	47	.130
4	.543[d]	.295	.234	1.86682	.059	3.877	1	46	.055
5	.646[e]	.417	.353	1.71635	.122	9.419	1	45	.004

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability

c. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

e. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	44.880	2	22.440	5.899	.005[c]
	Residual	182.600	48	3.804		
	Total	227.480	50			
3	Regression	53.657	3	17.886	4.836	.005[d]
	Residual	173.824	47	3.698		
	Total	227.480	50			
4	Regression	67.169	4	16.792	4.818	.002[e]
	Residual	160.311	46	3.485		
	Total	227.480	50			
5	Regression	94.917	5	18.983	6.444	.000[f]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability

d. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

e. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

f. Predictors: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	3.248	.850		3.820	.000
	Visitor or Resident	1.000	.557	.236	1.795	.079
	Water Landmark Identifiability	.239	.094	.335	2.546	.014
3	(Constant)	3.214	.839		3.832	.000
	Visitor or Resident	.818	.562	.193	1.457	.152
	Water Landmark Identifiability	.214	.094	.301	2.285	.027
	Canal Mappability	.157	.102	.205	1.540	.130
4	(Constant)	3.016	.820		3.676	.001
	Visitor or Resident	.693	.549	.164	1.263	.213
	Water Landmark Identifiability	.246	.092	.345	2.660	.011
	Canal Mappability	.198	.101	.258	1.950	.057
	River Mappability	.251	.127	.254	1.969	.055
5	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Water Landmark Identifiability	.269	.085	.377	3.149	.003
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
2	Canal Mappability	.205[c]	1.540	.130	.219	.916
	River Mappability	.204[c]	1.564	.125	.222	.957
	Aquaphilia Sensitivity Baseline	-.354[c]	-2.917	.005	-.392	.979
3	River Mappability	.254[d]	1.969	.055	.279	.918
	Aquaphilia Sensitivity Baseline	-.363[d]	-3.054	.004	-.411	.978
4	Aquaphilia Sensitivity Baseline	-.353[e]	-3.069	.004	-.416	.976

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability

d. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Water Landmark Identifiability, Canal Mappability, River Mappability

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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Canal Mappability[b]	.	Enter
3	River Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.389[b]	.151	.116	2.00592	.062	3.509	1	48	.067
3	.432[c]	.187	.135	1.98386	.036	2.073	1	47	.157
4	.543[d]	.295	.234	1.86682	.108	7.078	1	46	.011
5	.646[e]	.417	.353	1.71635	.122	9.419	1	45	.004

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Canal Mappability

c. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	34.343	2	17.171	4.268	.020[c]
	Residual	193.138	48	4.024		
	Total	227.480	50			
3	Regression	42.502	3	14.167	3.600	.020[d]
	Residual	184.978	47	3.936		
	Total	227.480	50			
4	Regression	67.169	4	16.792	4.818	.002[e]
	Residual	160.311	46	3.485		
	Total	227.480	50			
5	Regression	94.917	5	18.983	6.444	.000[f]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability

e. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

f. Predictors: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	3.278	.874		3.749	.000
	Visitor or Resident	1.001	.580	.237	1.727	.091
	Canal Mappability	.197	.105	.257	1.873	.067
3	(Constant)	3.134	.871		3.599	.001
	Visitor or Resident	.926	.576	.219	1.608	.114
	Canal Mappability	.232	.107	.302	2.173	.035
	River Mappability	.192	.133	.195	1.440	.157
4	(Constant)	3.016	.820		3.676	.001
	Visitor or Resident	.693	.549	.164	1.263	.213
	Canal Mappability	.198	.101	.258	1.950	.057
	River Mappability	.251	.127	.254	1.969	.055
	Water Landmark Identifiability	.246	.092	.345	2.660	.011
5	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Water Landmark Identifiability	.269	.085	.377	3.149	.003
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
2	River Mappability	.195[c]	1.440	.157	.206	.947
	Water Landmark Identifiability	.301[c]	2.285	.027	.316	.938
	Aquaphilia Sensitivity Baseline	-.332[c]	-2.625	.012	-.358	.987
3	Water Landmark Identifiability	.345[d]	2.660	.011	.365	.910
	Aquaphilia Sensitivity Baseline	-.322[d]	-2.569	.014	-.354	.984
4	Aquaphilia Sensitivity Baseline	-.353[e]	-3.069	.004	-.416	.976

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability

d. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Canal Mappability, River Mappability, Water Landmark Identifiability

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REGRESSION
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  /STATISTICS COEFF OUTS R ANOVA CHANGE
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  /NOORIGIN
  /DEPENDENT Coherence_2B
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  /METHOD=ENTER A1_C A1_R B1_M
  /METHOD=ENTER D1_R.
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident	.	Enter
2	River Mappability, Water Landmark Identifiability, Canal Mappability	.	Enter
3	Aquaphilia Sensitivity Baseline	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

Model Summary

				Std. Error of the Estimate	Change Statistics				
Model	R	R Square	Adjusted R Square		R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.543[b]	.295	.234	1.86682	.206	4.490	3	46	.008
3	.646[c]	.417	.353	1.71635	.122	9.419	1	45	.004

a. Predictors: (Constant), Visitor or Resident
b. Predictors: (Constant), Visitor or Resident, River Mappability, Water Landmark Identifiability, Canal Mappability
c. Predictors: (Constant), Visitor or Resident, River Mappability, Water Landmark Identifiability, Canal Mappability, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[a]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	67.169	4	16.792	4.818	.002[b]
	Residual	160.311	46	3.485		
	Total	227.480	50			
3	Regression	94.917	5	18.983	6.444	.000[c]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Predictors: (Constant), Visitor or Resident
b. Predictors: (Constant), Visitor or Resident, River Mappability, Water Landmark Identifiability, Canal Mappability
c. Predictors: (Constant), Visitor or Resident, River Mappability, Water Landmark Identifiability, Canal Mappability, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	3.016	.820		3.676	.001
	Visitor or Resident	.693	.549	.164	1.263	.213
	Canal Mappability	.198	.101	.258	1.950	.057
	River Mappability	.251	.127	.254	1.969	.055
	Water Landmark Identifiability	.246	.092	.345	2.660	.011
3	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Water Landmark Identifiability	.269	.085	.377	3.149	.003
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
2	Aquaphilia Sensitivity Baseline	-.353[c]	-3.069	.004	-.416	.976

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors in the Model: (Constant), Visitor or Resident
c. Predictors in the Model: (Constant), Visitor or Resident, River Mappability, Water Landmark Identifiability, Canal Mappability

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
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  /NOORIGIN
  /DEPENDENT Coherence_2B
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  /METHOD=ENTER D1_R
  /METHOD=ENTER A1_C A1_R B1_M.
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Aquaphilia Sensitivity Baseline[b]	.	Enter
3	River Mappability, Water Landmark Identifiability, Canal Mappability[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.434[b]	.188	.154	1.96156	.099	5.865	1	48	.019
3	.646[c]	.417	.353	1.71635	.229	5.898	3	45	.002

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, River Mappability, Water Landmark Identifiability, Canal Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	42.790	2	21.395	5.561	.007[c]
	Residual	184.690	48	3.848		
	Total	227.480	50			
3	Regression	94.917	5	18.983	6.444	.000[d]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors: (Constant), Visitor or Resident
c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline
d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, River Mappability, Water Landmark Identifiability, Canal Mappability

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	5.415	1.213		4.465	.000
	Visitor or Resident	1.127	.553	.266	2.038	.047
	Aquaphilia Sensitivity Baseline	-.907	.375	-.317	-2.422	.019
3	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Water Landmark Identifiability	.269	.085	.377	3.149	.003

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
2	Canal Mappability	.276[c]	2.130	.038	.297	.939
	River Mappability	.107[c]	.815	.419	.118	.994
	Water Landmark Identifiability	.372[c]	3.024	.004	.404	.956

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

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REGRESSION
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident	.	Enter
2	Aquaphilia Sensitivity Baseline	.	Enter
3	River Mappability, Water Landmark Identifiability, Canal Mappability	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.234[a]	.055	.035	3.10663	.055	2.827	1	49	.099
2	.321[b]	.103	.065	3.05766	.048	2.582	1	48	.115
3	.567[c]	.321	.246	2.74718	.218	4.821	3	45	.005

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, River Mappability, Water Landmark Identifiability, Canal Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.280	1	27.280	2.827	.099[b]
	Residual	472.906	49	9.651		
	Total	500.186	50			
2	Regression	51.421	2	25.710	2.750	.074[c]
	Residual	448.766	48	9.349		
	Total	500.186	50			
3	Regression	160.572	5	32.114	4.255	.003[d]
	Residual	339.615	45	7.547		
	Total	500.186	50			

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, River Mappability, Water Landmark Identifiability, Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.090	1.353		3.022	.004
	Visitor or Resident	1.465	.872	.234	1.681	.099
2	(Constant)	6.245	1.890		3.304	.002
	Visitor or Resident	1.326	.862	.211	1.538	.131
	Aquaphilia Sensitivity Baseline	-.939	.584	-.221	-1.607	.115
3	(Constant)	6.050	1.712		3.534	.001
	Visitor or Resident	.441	.813	.070	.542	.591
	Aquaphilia Sensitivity Baseline	-1.070	.528	-.252	-2.025	.049
	Canal Mappability	.306	.149	.269	2.053	.046
	River Mappability	.410	.188	.280	2.183	.034
	Water Landmark Identifiability	.365	.137	.345	2.670	.011

a. Dependent Variable: Average 12-Stage Coherence (12C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Aquaphilia Sensitivity Baseline	-.221[b]	-1.607	.115	-.226	.990
	Canal Mappability	.248[b]	1.768	.083	.247	.942
	River Mappability	.168[b]	1.211	.232	.172	.999
	Water Landmark Identifiability	.305[b]	2.247	.029	.309	.966
2	Canal Mappability	.261[c]	1.902	.063	.267	.939
	River Mappability	.153[c]	1.122	.268	.161	.994
	Water Landmark Identifiability	.332[c]	2.499	.016	.342	.956

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

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REGRESSION
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Aquaphilia Sensitivity Baseline[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.434[b]	.188	.154	1.96156	.099	5.865	1	48	.019

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	42.790	2	21.395	5.561	.007[c]
	Residual	184.690	48	3.848		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	5.415	1.213		4.465	.000
	Visitor or Resident	1.127	.553	.266	2.038	.047
	Aquaphilia Sensitivity Baseline	-.907	.375	-.317	-2.422	.019

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

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Error # 1.  Command name: /METHOD
The first word in the line is not recognized as an SPSS Statistics command.
Execution of this command stops.
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REGRESSION
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  /STATISTICS COEFF OUTS R ANOVA CHANGE
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  /NOORIGIN
  /DEPENDENT Coherence_2B
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  /METHOD=ENTER A1_R
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Aquaphilia Sensitivity Baseline[b]	.	Enter
3	Canal Mappability[b]	.	Enter
4	River Mappability[b]	.	Enter
5	Water Landmark Identifiability[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.434[b]	.188	.154	1.96156	.099	5.865	1	48	.019
3	.509[c]	.260	.212	1.89307	.071	4.536	1	47	.038
4	.537[d]	.289	.227	1.87532	.029	1.894	1	46	.175
5	.646[e]	.417	.353	1.71635	.128	9.916	1	45	.003

a. Predictors: (Constant), Visitor or Resident
b. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline
c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability
d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, River Mappability
e. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, River Mappability, Water Landmark Identifiability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	42.790	2	21.395	5.561	.007[c]
	Residual	184.690	48	3.848		
	Total	227.480	50			
3	Regression	59.045	3	19.682	5.492	.003[d]
	Residual	168.435	47	3.584		
	Total	227.480	50			
4	Regression	65.706	4	16.426	4.671	.003[e]
	Residual	161.775	46	3.517		
	Total	227.480	50			
5	Regression	94.917	5	18.983	6.444	.000[f]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability

e. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, River Mappability

f. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, River Mappability, Water Landmark Identifiability

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	5.415	1.213		4.465	.000
	Visitor or Resident	1.127	.553	.266	2.038	.047
	Aquaphilia Sensitivity Baseline	-.907	.375	-.317	-2.422	.019
3	(Constant)	5.458	1.171		4.663	.000
	Visitor or Resident	.841	.550	.199	1.527	.133
	Aquaphilia Sensitivity Baseline	-.951	.362	-.332	-2.625	.012
	Canal Mappability	.212	.099	.276	2.130	.038
4	(Constant)	5.263	1.168		4.505	.000
	Visitor or Resident	.777	.547	.184	1.421	.162
	Aquaphilia Sensitivity Baseline	-.923	.359	-.322	-2.569	.014
	Canal Mappability	.243	.101	.317	2.405	.020
	River Mappability	.174	.126	.176	1.376	.175
5	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004
	Canal Mappability	.206	.093	.269	2.215	.032
	River Mappability	.236	.117	.240	2.015	.050
	Water Landmark Identifiability	.269	.085	.377	3.149	.003

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
	Canal Mappability	.257[b]	1.873	.067	.261	.942
	River Mappability	.128[b]	.934	.355	.134	.999
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
2	Canal Mappability	.276[c]	2.130	.038	.297	.939
	River Mappability	.107[c]	.815	.419	.118	.994
	Water Landmark Identifiability	.372[c]	3.024	.004	.404	.956
3	River Mappability	.176[d]	1.376	.175	.199	.944
	Water Landmark Identifiability	.336[d]	2.758	.008	.377	.930
4	Water Landmark Identifiability	.377[e]	3.149	.003	.425	.903

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

d. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, River Mappability

```
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS R ANOVA CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT Coherence_2B
 /METHOD=ENTER TR
/METHOD=ENTER D1_R
 /METHOD=ENTER A1_C
 /METHOD=ENTER B1_M
  /METHOD=ENTER A1_R.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Aquaphilia Sensitivity Baseline[b]	.	Enter
3	Canal Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	River Mappability[b]	.	Enter

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.298[a]	.089	.070	2.05664	.089	4.781	1	49	.034
2	.434[b]	.188	.154	1.96156	.099	5.865	1	48	.019
3	.509[c]	.260	.212	1.89307	.071	4.536	1	47	.038
4	.604[d]	.365	.309	1.77255	.105	7.609	1	46	.008
5	.646[e]	.417	.353	1.71635	.053	4.062	1	45	.050

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability, River Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.222	1	20.222	4.781	.034[b]
	Residual	207.258	49	4.230		
	Total	227.480	50			
2	Regression	42.790	2	21.395	5.561	.007[c]
	Residual	184.690	48	3.848		
	Total	227.480	50			
3	Regression	59.045	3	19.682	5.492	.003[d]
	Residual	168.435	47	3.584		
	Total	227.480	50			
4	Regression	82.952	4	20.738	6.600	.000[e]
	Residual	144.528	46	3.142		
	Total	227.480	50			
5	Regression	94.917	5	18.983	6.444	.000[f]
	Residual	132.563	45	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)

b. Predictors: (Constant), Visitor or Resident

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability

e. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability

f. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability, River Mappability

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.331	.896		3.718	.001
	Visitor or Resident	1.262	.577	.298	2.187	.034
2	(Constant)	5.415	1.213		4.465	.000
	Visitor or Resident	1.127	.553	.266	2.038	.047
	Aquaphilia Sensitivity Baseline	-.907	.375	-.317	-2.422	.019
3	(Constant)	5.458	1.171		4.663	.000
	Visitor or Resident	.841	.550	.199	1.527	.133
	Aquaphilia Sensitivity Baseline	-.951	.362	-.332	-2.625	.012
	Canal Mappability	.212	.099	.276	2.130	.038
4	(Constant)	5.591	1.097		5.096	.000
	Visitor or Resident	.621	.522	.147	1.191	.240
	Aquaphilia Sensitivity Baseline	-1.040	.341	-.363	-3.054	.004
	Canal Mappability	.169	.094	.220	1.791	.080
	Water Landmark Identifiability	.240	.087	.336	2.758	.008
5	(Constant)	5.343	1.069		4.996	.000
	Visitor or Resident	.508	.508	.120	1.001	.322
	Aquaphilia Sensitivity Baseline	-1.013	.330	-.353	-3.069	.004
	Canal Mappability	.206	.093	.269	2.215	.032
	Water Landmark Identifiability	.269	.085	.377	3.149	.003
	River Mappability	.236	.117	.240	2.015	.050

a. Dependent Variable: Average 8-Stage Coherence (8C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Aquaphilia Sensitivity Baseline	-.317[b]	-2.422	.019	-.330	.990
	Canal Mappability	.257[b]	1.873	.067	.261	.942
	Water Landmark Identifiability	.335[b]	2.546	.014	.345	.966
	River Mappability	.128[b]	.934	.355	.134	.999
2	Canal Mappability	.276[c]	2.130	.038	.297	.939
	Water Landmark Identifiability	.372[c]	3.024	.004	.404	.956
	River Mappability	.107[c]	.815	.419	.118	.994
3	Water Landmark Identifiability	.336[d]	2.758	.008	.377	.930
	River Mappability	.176[d]	1.376	.175	.199	.944
4	River Mappability	.240[e]	2.015	.050	.288	.917

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors in the Model: (Constant), Visitor or Resident
c. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline
d. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability
e. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_2A
  /METHOD=ENTER TR
 /METHOD=ENTER D1_R
  /METHOD=ENTER A1_C
  /METHOD=ENTER B1_M
   /METHOD=ENTER A1_R.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Visitor or Resident[b]	.	Enter
2	Aquaphilia Sensitivity Baseline[b]	.	Enter
3	Canal Mappability[b]	.	Enter
4	Water Landmark Identifiability[b]	.	Enter
5	River Mappability[b]	.	Enter

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. All requested variables entered.

Model Summary

				Std.	Change Statistics				
Model	R	R Square	Adjusted R Square	Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.234[a]	.055	.035	3.10663	.055	2.827	1	49	.099
2	.321[b]	.103	.065	3.05766	.048	2.582	1	48	.115
3	.409[c]	.167	.114	2.97753	.064	3.618	1	47	.063
4	.499[d]	.249	.184	2.85735	.082	5.037	1	46	.030
5	.567[e]	.321	.246	2.74718	.072	4.764	1	45	.034

a. Predictors: (Constant), Visitor or Resident

b. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability

d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability

e. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability, River Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.280	1	27.280	2.827	.099[b]
	Residual	472.906	49	9.651		
	Total	500.186	50			
2	Regression	51.421	2	25.710	2.750	.074[c]
	Residual	448.766	48	9.349		
	Total	500.186	50			
3	Regression	83.498	3	27.833	3.139	.034[d]
	Residual	416.689	47	8.866		
	Total	500.186	50			
4	Regression	124.621	4	31.155	3.816	.009[e]
	Residual	375.565	46	8.164		
	Total	500.186	50			
5	Regression	160.572	5	32.114	4.255	.003[f]
	Residual	339.615	45	7.547		
	Total	500.186	50			

a. Dependent Variable: Average 12-Stage Coherence (12C)
b. Predictors: (Constant), Visitor or Resident
c. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline
d. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability
e. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability
f. Predictors: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability, River Mappability

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.090	1.353		3.022	.004
	Visitor or Resident	1.465	.872	.234	1.681	.099
2	(Constant)	6.245	1.890		3.304	.002
	Visitor or Resident	1.326	.862	.211	1.538	.131
	Aquaphilia Sensitivity Baseline	-.939	.584	-.221	-1.607	.115
3	(Constant)	6.306	1.841		3.425	.001
	Visitor or Resident	.924	.866	.147	1.067	.291
	Aquaphilia Sensitivity Baseline	-1.000	.570	-.235	-1.755	.086
	Canal Mappability	.297	.156	.261	1.902	.063
4	(Constant)	6.481	1.768		3.665	.001
	Visitor or Resident	.636	.841	.101	.756	.453
	Aquaphilia Sensitivity Baseline	-1.117	.549	-.263	-2.034	.048
	Canal Mappability	.241	.152	.212	1.587	.119
	Water Landmark Identifiability	.314	.140	.297	2.244	.030
5	(Constant)	6.050	1.712		3.534	.001
	Visitor or Resident	.441	.813	.070	.542	.591
	Aquaphilia Sensitivity Baseline	-1.070	.528	-.252	-2.025	.049
	Canal Mappability	.306	.149	.269	2.053	.046
	Water Landmark Identifiability	.365	.137	.345	2.670	.011
	River Mappability	.410	.188	.280	2.183	.034

a. Dependent Variable: Average 12-Stage Coherence (12C)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Aquaphilia Sensitivity Baseline	-.221[b]	-1.607	.115	-.226	.990
	Canal Mappability	.248[b]	1.768	.083	.247	.942
	Water Landmark Identifiability	.305[b]	2.247	.029	.309	.966
	River Mappability	.168[b]	1.211	.232	.172	.999
2	Canal Mappability	.261[c]	1.902	.063	.267	.939
	Water Landmark Identifiability	.332[c]	2.499	.016	.342	.956
	River Mappability	.153[c]	1.122	.268	.161	.994
3	Water Landmark Identifiability	.297[d]	2.244	.030	.314	.930
	River Mappability	.222[d]	1.649	.106	.236	.944
4	River Mappability	.280[e]	2.183	.034	.309	.917

a. Dependent Variable: Average 12-Stage Coherence (12C)

b. Predictors in the Model: (Constant), Visitor or Resident

c. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline

d. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability

e. Predictors in the Model: (Constant), Visitor or Resident, Aquaphilia Sensitivity Baseline, Canal Mappability, Water Landmark Identifiability

```
/* Stepwise Regression Analysis with Successive Removal of Variables*/
REGRESSION
  /MISSING MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_CWA
  /METHOD=STEPWISE A1_M A1_C A1_R A1_L A1_H B1_M B1_C B1_R B1_L
B1_H C1_M C1_C C1_R C1_L C1_H.
```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.573[a]	.329	.316	.89918

a. Predictors: (Constant), Canal Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.984	1	20.984	25.954	.000[b]
	Residual	42.852	53	.809		
	Total	63.836	54			

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

b. Predictors: (Constant), Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.633	.158		4.020	.000
	Canal Mappability	.229	.045	.573	5.094	.000

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Waterfront Landmark Mappability	-.161[b]	-1.422	.161	-.194	.966
	River Mappability	-.025[b]	-.216	.829	-.030	.961
	Lake Mappability	-.070[b]	-.618	.539	-.085	.987
	Harbour Mappability	.111[b]	.968	.338	.133	.970
	Water Landmark Identifiability	.033[b]	.286	.776	.040	.962
	Canal Identitifiability	.028[b]	.204	.839	.028	.671
	River Identitifiability	-.041[b]	-.362	.719	-.050	.983
	Lake Identifiability	-.009[b]	-.077	.939	-.011	.998
	Harbour Identifiability	-.044[b]	-.383	.703	-.053	.961
	Waterfront Landmark Attachment	-.168[b]	-1.504	.139	-.204	.994
	Canal Attachment	.012[b]	.094	.925	.013	.786
	River Attachment	.017[b]	.149	.882	.021	1.000
	Lake Attachment	.077[b]	.681	.499	.094	.996
	Harbour Attachment	-.104[b]	-.922	.361	-.127	.992

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

b. Predictors in the Model: (Constant), Canal Mappability

```
/* Stepwise Regression Analysis with Successive Addition of Variables*/

REGRESSION
  /MISSING MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_CWA
  /METHOD=STEPWISE A1_C A1_R B1_M
  /METHOD=ENTER D1_R
  /METHOD=ENTER H5_N
  /METHOD=ENTER H2
  /METHOD=ENTER AGE
  /METHOD=ENTER H13
  /METHOD=ENTER H14.
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Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Canal Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Aquaphilia Sensitivity Baseline	.	Enter
3	Length of Stay Normalized	.	Enter
4	Sex	.	Enter
5	Age	.	Enter
6	Income	.	Enter
7	Education	.	Enter

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.573[a]	.329	.316	.89918	.329	25.954	1	53	.000
2	.669[b]	.448	.426	.82344	.119	11.199	1	52	.002
3	.671[c]	.451	.418	.82919	.003	.280	1	51	.599
4	.674[d]	.455	.411	.83433	.004	.375	1	50	.543
5	.694[e]	.481	.428	.82211	.026	2.497	1	49	.120
6	.700[f]	.490	.426	.82349	.009	.836	1	48	.365
7	.723[g]	.522	.451	.80545	.032	3.174	1	47	.081

a. Predictors: (Constant), Canal Mappability

b. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline

c. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized

d. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex

e. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age

f. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income

g. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income, Education

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.984	1	20.984	25.954	.000[b]
	Residual	42.852	53	.809		
	Total	63.836	54			
2	Regression	28.578	2	14.289	21.074	.000[c]
	Residual	35.258	52	.678		
	Total	63.836	54			
3	Regression	28.771	3	9.590	13.948	.000[d]
	Residual	35.066	51	.688		
	Total	63.836	54			
4	Regression	29.031	4	7.258	10.426	.000[e]
	Residual	34.805	50	.696		
	Total	63.836	54			
5	Regression	30.719	5	6.144	9.090	.000[f]
	Residual	33.117	49	.676		
	Total	63.836	54			
6	Regression	31.286	6	5.214	7.689	.000[g]
	Residual	32.551	48	.678		
	Total	63.836	54			
7	Regression	33.345	7	4.764	7.343	.000[h]
	Residual	30.491	47	.649		
	Total	63.836	54			

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

b. Predictors: (Constant), Canal Mappability

c. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline

d. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized

e. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex

f. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age

g. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income

h. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income, Education

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.633	.158		4.020	.000
	Canal Mappability	.229	.045	.573	5.094	.000
2	(Constant)	1.713	.353		4.847	.000
	Canal Mappability	.233	.041	.584	5.660	.000
	Aquaphilia Sensitivity Baseline	-.524	.157	-.345	-3.347	.002
3	(Constant)	1.763	.368		4.788	.000
	Canal Mappability	.234	.042	.586	5.636	.000
	Aquaphilia Sensitivity Baseline	-.531	.158	-.350	-3.356	.001
	Length of Stay Normalized	-.042	.080	-.055	-.529	.599
4	(Constant)	1.929	.459		4.202	.000
	Canal Mappability	.228	.043	.570	5.302	.000
	Aquaphilia Sensitivity Baseline	-.504	.165	-.332	-3.051	.004
	Length of Stay Normalized	-.043	.080	-.056	-.537	.594
	Sex	-.154	.252	-.068	-.612	.543
5	(Constant)	1.792	.460		3.892	.000
	Canal Mappability	.239	.043	.599	5.572	.000
	Aquaphilia Sensitivity Baseline	-.470	.164	-.309	-2.859	.006
	Length of Stay Normalized	-.050	.079	-.065	-.627	.534
	Sex	-.083	.252	-.037	-.329	.744
	Age	-.001	.000	-.170	-1.580	.120
6	(Constant)	1.627	.495		3.283	.002
	Canal Mappability	.239	.043	.599	5.560	.000
	Aquaphilia Sensitivity Baseline	-.490	.166	-.323	-2.951	.005
	Length of Stay Normalized	-.060	.080	-.078	-.746	.459
	Sex	-.087	.253	-.038	-.344	.733
	Age	-.001	.000	-.187	-1.709	.094
	Income	.090	.099	.098	.914	.365

7	(Constant)	.857	.649		1.319	.194
	Canal Mappability	.233	.042	.582	5.505	.000
	Aquaphilia Sensitivity Baseline	-.499	.162	-.329	-3.075	.004
	Length of Stay Normalized	-.043	.079	-.056	-.540	.592
	Sex	-.033	.249	-.015	-.132	.895
	Age	-.001	.000	-.204	-1.898	.064
	Income	.019	.105	.021	.182	.856
	Education	.229	.128	.200	1.782	.081

a. Dependent Variable: Average Water-Based Allocentric Coherence

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	River Mappability	-.025[b]	-.216	.829	-.030	.961
	Water Landmark Identifiability	.033[b]	.286	.776	.040	.962
	Aquaphilia Sensitivity Baseline	-.345[b]	-3.347	.002	-.421	.999
	Length of Stay Normalized	-.025[b]	-.224	.823	-.031	.999
	Sex	-.157[b]	-1.374	.175	-.187	.952
	Age	-.232[b]	-2.109	.040	-.281	.982
	Income	-.002[b]	-.015	.988	-.002	.999
	Education	.154[b]	1.365	.178	.186	.983
2	River Mappability	-.048[c]	-.447	.656	-.063	.957
	Water Landmark Identifiability	.060[c]	.566	.574	.079	.957
	Length of Stay Normalized	-.055[c]	-.529	.599	-.074	.992
	Sex	-.067[c]	-.607	.547	-.085	.883
	Age	-.173[c]	-1.659	.103	-.226	.948
	Income	.056[c]	.529	.599	.074	.973
	Education	.186[c]	1.822	.074	.247	.975
3	River Mappability	-.050[d]	-.463	.645	-.065	.956
	Water Landmark Identifiability	.073[d]	.674	.504	.095	.923

	Sex	-.068[d]	-.612	.543	-.086	.883
	Age	-.176[d]	-1.681	.099	-.231	.945
	Income	.064[d]	.597	.553	.084	.957
	Education	.183[d]	1.775	.082	.244	.971
4	River Mappability	-.042[e]	-.387	.700	-.055	.941
	Water Landmark Identifiability	.081[e]	.736	.465	.105	.913
	Age	-.170[e]	-1.580	.120	-.220	.915
	Income	.067[e]	.623	.536	.089	.955
	Education	.179[e]	1.717	.092	.238	.965
5	River Mappability	-.053[f]	-.495	.623	-.071	.937
	Water Landmark Identifiability	.058[f]	.525	.602	.076	.894
	Income	.098[f]	.914	.365	.131	.928
	Education	.208[f]	2.024	.049	.280	.944
6	River Mappability	-.066[g]	-.612	.544	-.089	.923
	Water Landmark Identifiability	.040[g]	.361	.720	.053	.863
	Education	.200[g]	1.782	.081	.252	.806
7	River Mappability	-.123[h]	-1.136	.262	-.165	.860
	Water Landmark Identifiability	.035[h]	.320	.751	.047	.863

a. Dependent Variable: Average Water-Based Allocentric Coherence
b. Predictors in the Model: (Constant), Canal Mappability
c. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline
d. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized
e. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex
f. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age
g. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income
h. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income, Education

/* Final Regression Analysis with IVs identified by Stepwise Regression Analyses.*/

```
REGRESSION
  /MISSING MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_CWA
  /METHOD=ENTER A1_C D1_R
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /SAVE PRED ZPRED COOK LEVER RESID DFBETA SDBETA.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Aquaphilia Sensitivity Baseline, Canal Mappability[b]	.	Enter

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.669[a]	.448	.426	.82344

a. Predictors: (Constant), Aquaphilia Sensitivity Baseline, Canal Mappability

b. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.578	2	14.289	21.074	.000[b]
	Residual	35.258	52	.678		
	Total	63.836	54			

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)

b. Predictors: (Constant), Aquaphilia Sensitivity Baseline, Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1.713	.353		4.847	.000		
	Canal Mappability	.233	.041	.584	5.660	.000	.999	1.001
	Aquaphilia Sensitivity Baseline	-.524	.157	-.345	-3.347	.002	.999	1.001

a. Dependent Variable: Average Water-Based Allocentric Coherence

Collinearity Diagnostics[a]

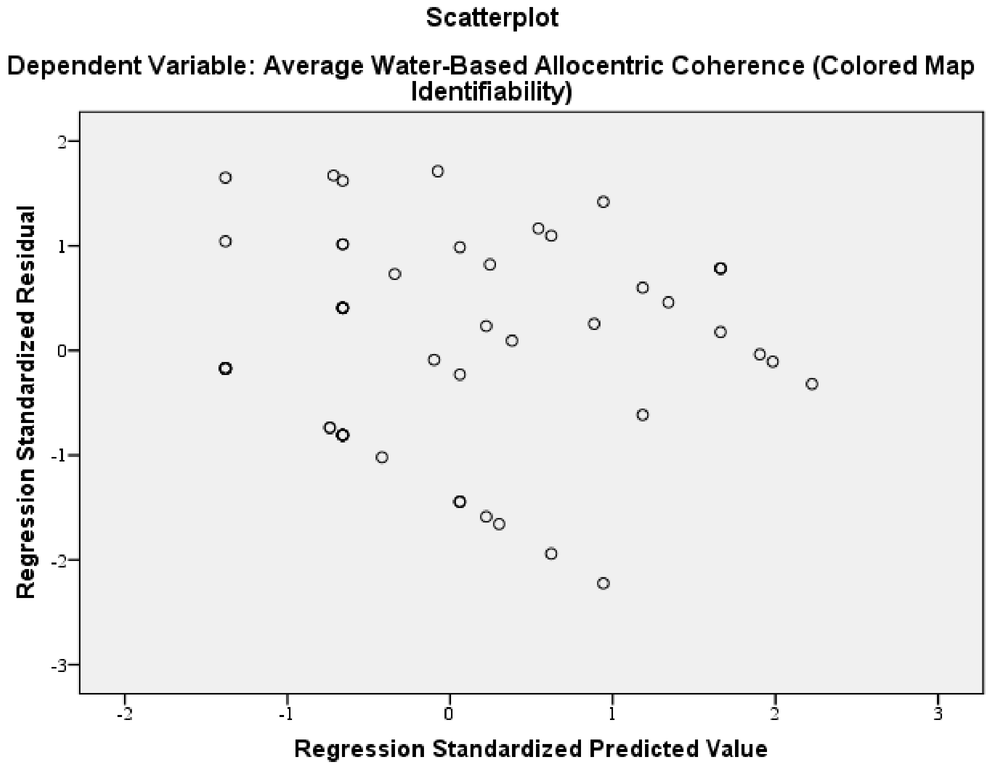
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Variance Proportions Canal Mappability	Variance Proportions Aquaphilia Sensitivity Baseline
1	1	2.476	1.000	.01	.06	.02
	2	.471	2.292	.02	.92	.03
	3	.053	6.838	.96	.01	.95

a. Dependent Variable: Average Water-Based Allocentric Coherence

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.1411	2.7637	1.1455	.72748	55
Std. Predicted Value	-1.381	2.224	.000	1.000	55
Standard Error of Predicted Value	.111	.301	.186	.048	55
Adjusted Predicted Value	.0504	2.8042	1.1461	.72704	55
Residual	-1.83096	1.40966	.00000	.80804	55
Std. Residual	-2.224	1.712	.000	.981	55
Stud. Residual	-2.267	1.728	.000	1.005	55
Deleted Residual	-1.90257	1.44956	-.00064	.84718	55
Stud. Deleted Residual	-2.365	1.762	-.002	1.018	55
Mahal. Distance	.008	6.211	1.964	1.537	55
Cook's Distance	.000	.067	.016	.019	55
Centered Leverage Value	.000	.115	.036	.028	55

a. Dependent Variable: Average Water-Based Allocentric Coherence (Colored Map Identifiability)



/* Stepwise Regression Analysis with Successive Removal of Variables*/

```
REGRESSION
  /MISSING MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_CWE
  /METHOD=STEPWISE A1_M A1_C A1_R A1_L A1_H B1_M B1_C B1_R B1_L
B1_H C1_M C1_C C1_R C1_L C1_H.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Canal Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Lake Attachment	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Water-Based Egocentric Coherence

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.438[a]	.192	.177	.67195
2	.505[b]	.255	.226	.65135

a. Predictors: (Constant), Canal Mappability
b. Predictors: (Constant), Canal Mappability, Lake Attachment

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.678	1	5.678	12.576	.001[b]
	Residual	23.931	53	.452		
	Total	29.609	54			
2	Regression	7.547	2	3.774	8.895	.000[c]
	Residual	22.062	52	.424		
	Total	29.609	54			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)
b. Predictors: (Constant), Canal Mappability
c. Predictors: (Constant), Canal Mappability, Lake Attachment

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.606	.118		13.646	.000
	Canal Mappability	.119	.034	.438	3.546	.001
2	(Constant)	1.546	.118		13.141	.000
	Canal Mappability	.115	.033	.421	3.511	.001
	Lake Attachment	.114	.054	.252	2.099	.041

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Waterfront Landmark Mappability	-.144[b]	-1.153	.254	-.158	.966
	River Mappability	.000[b]	.001	.999	.000	.961
	Lake Mappability	.164[b]	1.330	.189	.181	.987
	Harbour Mappability	.119[b]	.952	.346	.131	.970
	Water Landmark Identifiability	.066[b]	.521	.604	.072	.962
	Canal Identitifiability	.002[b]	.011	.991	.002	.671
	River Identitifiability	.149[b]	1.199	.236	.164	.983
	Lake Identifiability	.246[b]	2.045	.046	.273	.998
	Harbour Identifiability	.027[b]	.212	.833	.029	.961
	Waterfront Landmark Attachment	-.037[b]	-.298	.767	-.041	.994
	Canal Attachment	.206[b]	1.497	.140	.203	.786
	River Attachment	-.060[b]	-.481	.632	-.067	1.000
	Lake Attachment	.252[b]	2.099	.041	.279	.996
	Harbour Attachment	.006[b]	.047	.962	.007	.992
2	Waterfront Landmark Mappability	-.090[c]	-.718	.476	-.100	.915
	River Mappability	.044[c]	.355	.724	.050	.934
	Lake Mappability	.069[c]	.512	.611	.072	.807
	Harbour Mappability	.036[c]	.275	.784	.038	.855
	Water Landmark Identifiability	.093[c]	.751	.456	.105	.953
	Canal Identitifiability	.038[c]	.257	.798	.036	.661
	River Identitifiability	.183[c]	1.524	.134	.209	.968
	Lake Identifiability	.128[c]	.679	.501	.095	.409
	Harbour Identifiability	-.183[c]	-1.227	.225	-.169	.638
	Waterfront Landmark Attachment	-.020[c]	-.161	.873	-.022	.989
	Canal Attachment	.243[c]	1.827	.074	.248	.775
	River Attachment	-.040[c]	-.329	.743	-.046	.993
	Harbour Attachment	-.132[c]	-.984	.330	-.137	.796

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)
b. Predictors in the Model: (Constant), Canal Mappability
c. Predictors in the Model: (Constant), Canal Mappability, Lake Attachment

```
/* Stepwise Regression Analysis with Successive Addition of Variables*/

REGRESSION
  /MISSING MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_CWE
  /METHOD=STEPWISE A1_C A1_R B1_M
  /METHOD=ENTER D1_R
  /METHOD=ENTER H5_N
  /METHOD=ENTER H2
  /METHOD=ENTER AGE
  /METHOD=ENTER H13
  /METHOD=ENTER H14.
```

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Canal Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Aquaphilia Sensitivity Baseline[b]	.	Enter
3	Length of Stay Normalized[b]	.	Enter
4	Sex[b]	.	Enter
5	Age[b]	.	Enter
6	Income[b]	.	Enter
7	Education[b]	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)
b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	.438[a]	.192	.177	.67195	.192	12.576	1	53	.001
2	.535[b]	.286	.259	.63761	.094	6.864	1	52	.012
3	.542[c]	.294	.252	.64022	.008	.577	1	51	.451
4	.546[d]	.299	.242	.64449	.005	.326	1	50	.571
5	.573[e]	.328	.260	.63709	.030	2.169	1	49	.147
6	.641[f]	.410	.337	.60310	.082	6.679	1	48	.013
7	.645[g]	.416	.329	.60646	.006	.469	1	47	.497

a. Predictors: (Constant), Canal Mappability
b. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline
c. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized
d. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex
e. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age
f. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income
g. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income, Education

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.678	1	5.678	12.576	.001[b]
	Residual	23.931	53	.452		
	Total	29.609	54			
2	Regression	8.469	2	4.234	10.416	.000[c]
	Residual	21.140	52	.407		
	Total	29.609	54			
3	Regression	8.705	3	2.902	7.079	.000[d]
	Residual	20.904	51	.410		
	Total	29.609	54			
4	Regression	8.841	4	2.210	5.321	.001[e]
	Residual	20.768	50	.415		
	Total	29.609	54			

5	Regression	9.721	5	1.944	4.790	.001[f]
	Residual	19.888	49	.406		
	Total	29.609	54			
6	Regression	12.150	6	2.025	5.567	.000[g]
	Residual	17.459	48	.364		
	Total	29.609	54			
7	Regression	12.323	7	1.760	4.786	.000[h]
	Residual	17.286	47	.368		
	Total	29.609	54			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors: (Constant), Canal Mappability

c. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline

d. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized

e. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex

f. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age

g. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income

h. Predictors: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income, Education

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.606	.118		13.646	.000
	Canal Mappability	.119	.034	.438	3.546	.001
2	(Constant)	2.261	.274		8.261	.000
	Canal Mappability	.122	.032	.447	3.814	.000
	Aquaphilia Sensitivity Baseline	-.318	.121	-.307	-2.620	.012
3	(Constant)	2.316	.284		8.148	.000
	Canal Mappability	.123	.032	.450	3.823	.000
	Aquaphilia Sensitivity Baseline	-.325	.122	-.315	-2.664	.010

	Length of Stay Normalized	-.047	.062	-.090	-.759	.451
4	(Constant)	2.436	.355		6.869	.000
	Canal Mappability	.118	.033	.434	3.558	.001
	Aquaphilia Sensitivity Baseline	-.306	.128	-.296	-2.398	.020
	Length of Stay Normalized	-.048	.062	-.091	-.765	.448
	Sex	-.111	.195	-.072	-.571	.571
5	(Constant)	2.337	.357		6.549	.000
	Canal Mappability	.126	.033	.465	3.798	.000
	Aquaphilia Sensitivity Baseline	-.281	.127	-.272	-2.209	.032
	Length of Stay Normalized	-.052	.061	-.100	-.849	.400
	Sex	-.060	.195	-.039	-.305	.761
	Age	-.001	.000	-.180	-1.473	.147
6	(Constant)	1.994	.363		5.496	.000
	Canal Mappability	.126	.032	.464	4.004	.000
	Aquaphilia Sensitivity Baseline	-.323	.122	-.313	-2.659	.011
	Length of Stay Normalized	-.073	.059	-.140	-1.245	.219
	Sex	-.068	.185	-.044	-.366	.716
	Age	-.001	.000	-.232	-1.969	.055
	Income	.187	.072	.297	2.584	.013
7	(Constant)	1.772	.489		3.623	.001
	Canal Mappability	.124	.032	.457	3.905	.000
	Aquaphilia Sensitivity Baseline	-.326	.122	-.315	-2.665	.011
	Length of Stay Normalized	-.068	.060	-.131	-1.146	.258
	Sex	-.052	.187	-.034	-.278	.782
	Age	-.001	.000	-.239	-2.011	.050
	Income	.167	.079	.265	2.113	.040
	Education	.066	.097	.085	.685	.497

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	River Mappability	.000[b]	.001	.999	.000	.961
	Water Landmark Identifiability	.066[b]	.521	.604	.072	.962
	Aquaphilia Sensitivity Baseline	-.307[b]	-2.620	.012	-.341	.999
	Length of Stay Normalized	-.063[b]	-.506	.615	-.070	.999
	Sex	-.150[b]	-1.188	.240	-.163	.952
	Age	-.233[b]	-1.918	.061	-.257	.982
	Income	.184[b]	1.504	.139	.204	.999
	Education	.137[b]	1.099	.277	.151	.983
2	River Mappability	-.020[c]	-.164	.871	-.023	.957
	Water Landmark Identifiability	.090[c]	.751	.456	.105	.957
	Length of Stay Normalized	-.090[c]	-.759	.451	-.106	.992
	Sex	-.070[c]	-.560	.578	-.078	.883
	Age	-.181[c]	-1.526	.133	-.209	.948
	Income	.240[c]	2.081	.042	.280	.973
	Education	.165[c]	1.406	.166	.193	.975
3	River Mappability	-.023[d]	-.190	.850	-.027	.956
	Water Landmark Identifiability	.111[d]	.908	.368	.127	.923
	Sex	-.072[d]	-.571	.571	-.081	.883
	Age	-.187[d]	-1.566	.124	-.216	.945
	Income	.255[d]	2.201	.032	.297	.957
	Education	.160[d]	1.351	.183	.188	.971
4	River Mappability	-.015[e]	-.119	.906	-.017	.941
	Water Landmark Identifiability	.120[e]	.966	.339	.137	.913
	Age	-.180[e]	-1.473	.147	-.206	.915
	Income	.259[e]	2.221	.031	.302	.955
	Education	.156[e]	1.299	.200	.182	.965
5	River Mappability	-.026[f]	-.214	.832	-.031	.937

	Water Landmark Identifiability	.096[f]	.771	.444	.111	.894
	Income	.297[f]	2.584	.013	.349	.928
	Education	.185[f]	1.560	.125	.220	.944
6	River Mappability	-.064[g]	-.549	.586	-.080	.923
	Water Landmark Identifiability	.041[g]	.339	.736	.049	.863
	Education	.085[g]	.685	.497	.099	.806
7	River Mappability	-.091[h]	-.751	.457	-.110	.860
	Water Landmark Identifiability	.039[h]	.319	.751	.047	.863

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors in the Model: (Constant), Canal Mappability

c. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline

d. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized

e. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex

f. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age

g. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income

h. Predictors in the Model: (Constant), Canal Mappability, Aquaphilia Sensitivity Baseline, Length of Stay Normalized, Sex, Age, Income, Education

```
/* Final Regression Analysis with IVs identified by Stepwise Regression Analyses.*/

REGRESSION
  /MISSING MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_CWE
  /METHOD=ENTER A1_C D1_R
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /SAVE PRED ZPRED COOK LEVER RESID DFBETA SDBETA.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Aquaphilia Sensitivity Baseline, Canal Mappability	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.535[a]	.286	.259	.63761

a. Predictors: (Constant), Aquaphilia Sensitivity Baseline, Canal Mappability
b. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.469	2	4.234	10.416	.000[b]
	Residual	21.140	52	.407		
	Total	29.609	54			

a. Dependent Variable: Water-Based Egocentric Coherence
b. Predictors: (Constant), Aquaphilia Sensitivity Baseline, Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2.261	.274		8.261	.000		
	Canal Mappability	.122	.032	.447	3.814	.000	.999	1.001
	Aquaphilia Sensitivity Baseline	-.318	.121	-.307	-2.620	.012	.999	1.001

a. Dependent Variable: Water-Based Egocentric Coherence

Collinearity Diagnostics[a]

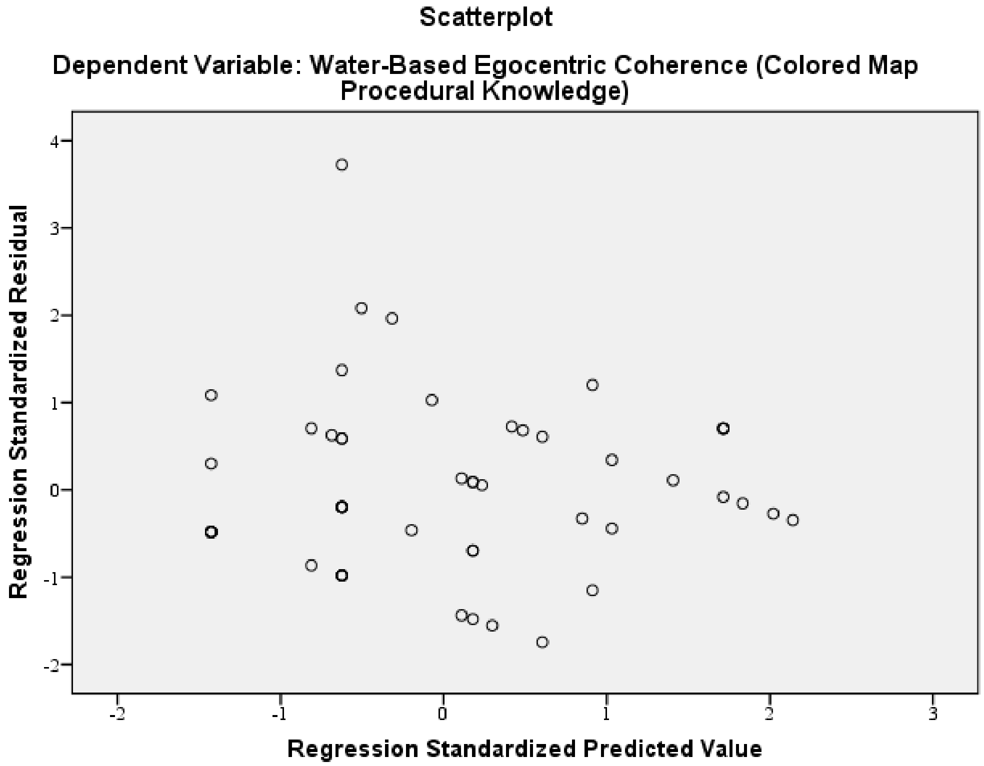
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Canal Mappability	Aquaphilia Sensitivity Baseline
1	1	2.476	1.000	.01	.06	.02
	2	.471	2.292	.02	.92	.03
	3	.053	6.838	.96	.01	.95

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.3080	2.7204	1.8727	.39602	55
Std. Predicted Value	-1.426	2.141	.000	1.000	55
Standard Error of Predicted Value	.086	.233	.144	.037	55
Adjusted Predicted Value	1.2618	2.7543	1.8738	.39612	55
Residual	-1.11218	2.37441	.00000	.62569	55
Std. Residual	-1.744	3.724	.000	.981	55
Stud. Residual	-1.768	3.783	-.001	1.002	55
Deleted Residual	-1.14219	2.44992	-.00108	.65232	55
Stud. Deleted Residual	-1.806	4.400	.012	1.055	55
Mahal. Distance	.008	6.211	1.964	1.537	55
Cook's Distance	.000	.152	.014	.024	55
Centered Leverage Value	.000	.115	.036	.028	55

a. Dependent Variable: Water-Based Egocentric Coherence

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  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT D1_R
  /METHOD=STEPWISE H5_N AGE H2 H13 H14.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Canal Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Length of Stay Normalized	.	Enter
3	Gender	.	Enter
4	Age	.	Enter
5	Income	.	Enter
6	Education	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.438[a]	.192	.177	.67195	.192	12.576	1	53	.001
2	.442[b]	.196	.165	.67672	.004	.256	1	52	.615
3	.467[c]	.218	.172	.67385	.022	1.444	1	51	.235
4	.511[d]	.261	.202	.66134	.044	2.947	1	50	.092
5	.569[e]	.324	.254	.63935	.062	4.499	1	49	.039
6	.573[f]	.328	.244	.64386	.004	.316	1	48	.576

a. Predictors: (Constant), Canal Mappability

b. Predictors: (Constant), Canal Mappability, Length of Stay Normalized

c. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender

d. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age

e. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age, Income

f. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age, Income, Education

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.678	1	5.678	12.576	.001[b]
	Residual	23.931	53	.452		
	Total	29.609	54			
2	Regression	5.796	2	2.898	6.328	.003[c]
	Residual	23.813	52	.458		
	Total	29.609	54			
3	Regression	6.451	3	2.150	4.736	.005[d]
	Residual	23.158	51	.454		
	Total	29.609	54			
4	Regression	7.740	4	1.935	4.424	.004[e]
	Residual	21.869	50	.437		
	Total	29.609	54			
5	Regression	9.579	5	1.916	4.687	.001[f]
	Residual	20.030	49	.409		
	Total	29.609	54			
6	Regression	9.710	6	1.618	3.904	.003[g]
	Residual	19.899	48	.415		
	Total	29.609	54			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors: (Constant), Canal Mappability

c. Predictors: (Constant), Canal Mappability, Length of Stay Normalized

d. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender

e. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age

f. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age, Income

g. Predictors: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age, Income, Education

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.606	.118		13.646	.000
	Canal Mappability	.119	.034	.438	3.546	.001
2	(Constant)	1.634	.130		12.537	.000
	Canal Mappability	.120	.034	.440	3.536	.001
	Length of Stay Normalized	-.033	.065	-.063	-.506	.615
3	(Constant)	1.974	.311		6.341	.000
	Canal Mappability	.111	.035	.407	3.203	.002
	Length of Stay Normalized	-.036	.065	-.069	-.556	.580
	Gender	-.236	.196	-.153	-1.202	.235
4	(Constant)	1.900	.308		6.162	.000
	Canal Mappability	.121	.034	.446	3.522	.001
	Length of Stay Normalized	-.043	.064	-.082	-.672	.505
	Gender	-.162	.197	-.105	-.820	.416
	Age	-.001	.000	-.216	-1.717	.092
5	(Constant)	1.549	.341		4.539	.000
	Canal Mappability	.121	.033	.443	3.616	.001
	Length of Stay Normalized	-.060	.062	-.114	-.961	.341
	Gender	-.182	.191	-.118	-.953	.345
	Age	-.001	.000	-.265	-2.139	.037
	Income	.161	.076	.256	2.121	.039
6	(Constant)	1.351	.491		2.750	.008
	Canal Mappability	.119	.034	.437	3.525	.001
	Length of Stay Normalized	-.055	.063	-.106	-.877	.385
	Gender	-.169	.193	-.110	-.874	.387
	Age	-.001	.000	-.272	-2.167	.035
	Income	.143	.083	.228	1.722	.091
	Education	.058	.103	.074	.562	.576

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	River Mappability	.000[b]	.001	.999	.000	.961
	Water Landmark Identifiability	.066[b]	.521	.604	.072	.962
	Length of Stay Normalized	-.063[b]	-.506	.615	-.070	.999
	Gender	-.150[b]	-1.188	.240	-.163	.952
	Age	-.233[b]	-1.918	.061	-.257	.982
	Income	.184[b]	1.504	.139	.204	.999
	Education	.137[b]	1.099	.277	.151	.983
2	River Mappability	-.002[c]	-.014	.989	-.002	.960
	Water Landmark Identifiability	.080[c]	.619	.539	.086	.931
	Gender	-.153[c]	-1.202	.235	-.166	.950
	Age	-.239[c]	-1.949	.057	-.263	.978
	Income	.193[c]	1.563	.124	.214	.987
	Education	.133[c]	1.056	.296	.146	.978
3	River Mappability	.014[d]	.108	.914	.015	.950
	Water Landmark Identifiability	.101[d]	.776	.442	.109	.917
	Age	-.216[d]	-1.717	.092	-.236	.931
	Income	.208[d]	1.695	.096	.233	.979
	Education	.125[d]	.994	.325	.139	.975
4	River Mappability	-.002[e]	-.019	.985	-.003	.945
	Water Landmark Identifiability	.073[e]	.565	.575	.080	.900
	Income	.256[e]	2.121	.039	.290	.945
	Education	.162[e]	1.311	.196	.184	.951
5	River Mappability	-.031[f]	-.254	.801	-.037	.933
	Water Landmark Identifiability	.022[f]	.176	.861	.025	.866
	Education	.074[f]	.562	.576	.081	.807
6	River Mappability	-.052[g]	-.408	.685	-.059	.872
	Water Landmark Identifiability	.020[g]	.159	.875	.023	.865

a. Dependent Variable: Water-Based Egocentric Coherence

b. Predictors in the Model: (Constant), Canal Mappability
c. Predictors in the Model: (Constant), Canal Mappability, Length of Stay Normalized
d. Predictors in the Model: (Constant), Canal Mappability, Length of Stay Normalized, Gender
e. Predictors in the Model: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age
f. Predictors in the Model: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age, Income
g. Predictors in the Model: (Constant), Canal Mappability, Length of Stay Normalized, Gender, Age, Income, Education

```
/* Final Regression Analysis with IVs identified by Previous Stepwise Regression
Analyses.*/

REGRESSION
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  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL
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  /NOORIGIN
  /DEPENDENT Coherence_CWE
  /METHOD=ENTER A1_C D1_R
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /SAVE PRED ZPRED COOK LEVER RESID DFBETA SDBETA.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Aquaphilia Sensitivity Baseline, Canal Mappability[b]	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.535[a]	.286	.259	.63761

a. Predictors: (Constant), Aquaphilia Sensitivity Baseline, Canal Mappability
b. Dependent Variable: Water-Based Egocentric Coherence

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.469	2	4.234	10.416	.000[b]
	Residual	21.140	52	.407		
	Total	29.609	54			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors: (Constant), Aquaphilia Sensitivity Baseline, Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2.261	.274		8.261	.000		
	Canal Mappability	.122	.032	.447	3.814	.000	.999	1.001
	Aquaphilia Sensitivity Baseline	-.318	.121	-.307	-2.620	.012	.999	1.001

a. Dependent Variable: Water-Based Egocentric Coherence

Collinearity Diagnostics[a]

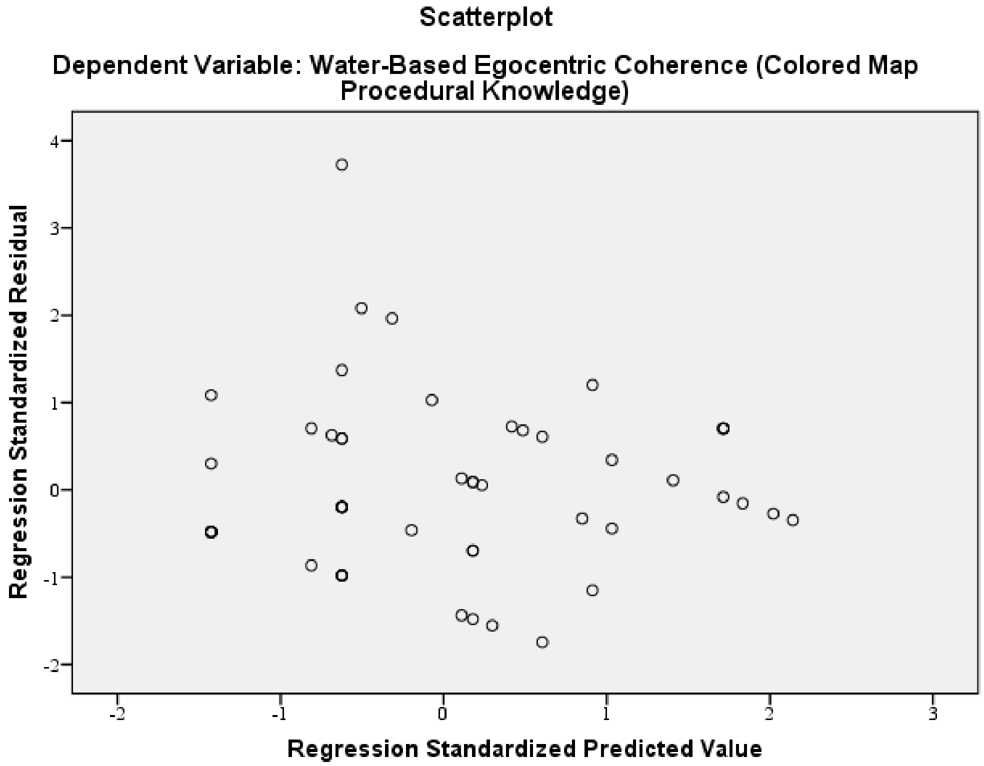
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Canal Mappability	Aquaphilia Sensitivity Baseline
1	1	2.476	1.000	.01	.06	.02
	2	.471	2.292	.02	.92	.03
	3	.053	6.838	.96	.01	.95

a. Dependent Variable: Water-Based Egocentric Coherence

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.3080	2.7204	1.8727	.39602	55
Std. Predicted Value	-1.426	2.141	.000	1.000	55
Standard Error of Predicted Value	.086	.233	.144	.037	55
Adjusted Predicted Value	1.2618	2.7543	1.8738	.39612	55
Residual	-1.11218	2.37441	.00000	.62569	55
Std. Residual	-1.744	3.724	.000	.981	55
Stud. Residual	-1.768	3.783	-.001	1.002	55
Deleted Residual	-1.14219	2.44992	-.00108	.65232	55
Stud. Deleted Residual	-1.806	4.400	.012	1.055	55
Mahal. Distance	.008	6.211	1.964	1.537	55
Cook's Distance	.000	.152	.014	.024	55
Centered Leverage Value	.000	.115	.036	.028	55

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)



/* Final Regression Analysis with IVs identified by Stepwise Regression Analyses.*/

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  /NOORIGIN
  /DEPENDENT Coherence_CWE
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  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /SAVE PRED ZPRED COOK LEVER RESID DFBETA SDBETA.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Income, Canal Mappability, Aquaphilia Sensitivity Baseline, Age[b]	.	Enter

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.624[a]	.390	.341	.60113

a. Predictors: (Constant), Income, Canal Mappability, Aquaphilia Sensitivity Baseline, Age

b. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.541	4	2.885	7.984	.000[b]
	Residual	18.068	50	.361		
	Total	29.609	54			

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

b. Predictors: (Constant), Income, Canal Mappability, Aquaphilia Sensitivity Baseline, Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1.862	.297		6.272	.000		
	Canal Mappability	.128	.030	.469	4.207	.000	.982	1.018
	Aquaphilia Sensitivity Baseline	-.320	.117	-.310	-2.727	.009	.947	1.056
	Age	-.001	.000	-.228	-1.980	.053	.922	1.085
	Income	.174	.071	.277	2.438	.018	.946	1.057

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Collinearity Diagnostics[a]

Dimension	Eigen-value	Condition Index	Variance Proportions (Constant)	Canal Mappability	Aquaphilia Sensitivity Baseline	Age	Income
1	3.452	1.000	.01	.03	.01	.01	.01
2	.864	1.999	.00	.00	.00	.93	.00
3	.511	2.598	.01	.94	.01	.01	.02
4	.125	5.246	.03	.01	.25	.01	.84
5	.048	8.513	.95	.02	.73	.04	.12

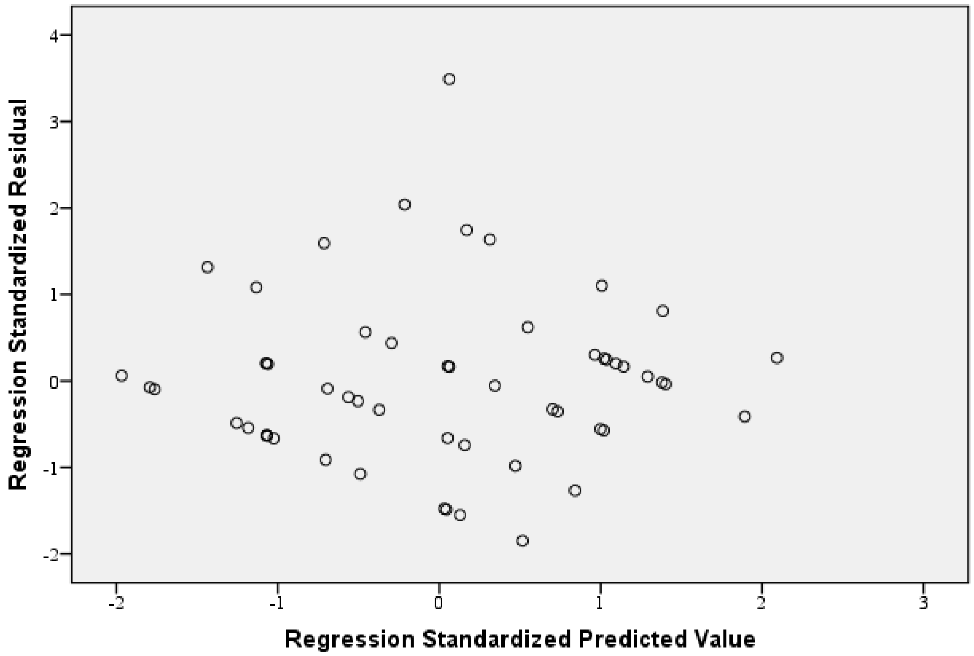
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.9634	2.8399	1.8727	.46230	55
Std. Predicted Value	-1.967	2.092	.000	1.000	55
Standard Error of Predicted Value	.090	.600	.168	.068	55
Adjusted Predicted Value	-10.1489	2.8174	1.6703	1.68311	55
Residual	-1.11132	2.09844	.00000	.57844	55
Std. Residual	-1.849	3.491	.000	.962	55
Stud. Residual	-1.872	3.609	.019	1.002	55
Deleted Residual	-1.13957	11.14894	.20247	1.62427	55
Stud. Deleted Residual	-1.922	4.155	.030	1.050	55
Mahal. Distance	.234	52.841	3.927	6.916	55
Cook's Distance	.000	68.568	1.259	9.244	55
Centered Leverage Value	.004	.979	.073	.128	55

a. Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

Scatterplot

Dependent Variable: Water-Based Egocentric Coherence (Colored Map Procedural Knowledge)

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REGRESSION
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  /NOORIGIN
  /DEPENDENT Coherence_2B
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B1_H C1_M C1_C C1_R C1_L C1_H.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Water Landmark Identifiability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	River Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Canal Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Coherence Score 2B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.365[a]	.133	.117	2.00472
2	.452[b]	.204	.173	1.93941
3	.533[c]	.284	.241	1.85800

a. Predictors: (Constant), Water Landmark Identifiability
b. Predictors: (Constant), Water Landmark Identifiability, River Mappability
c. Predictors: (Constant), Water Landmark Identifiability, River Mappability, Canal Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	32.743	1	32.743	8.147	.006[b]
	Residual	213.002	53	4.019		
	Total	245.745	54			
2	Regression	50.157	2	25.079	6.668	.003[c]
	Residual	195.588	52	3.761		
	Total	245.745	54			
3	Regression	69.685	3	23.228	6.729	.001[d]
	Residual	176.060	51	3.452		
	Total	245.745	54			

a. Dependent Variable: Coherence Score 2B
b. Predictors: (Constant), Water Landmark Identifiability
c. Predictors: (Constant), Water Landmark Identifiability, River Mappability
d. Predictors: (Constant), Water Landmark Identifiability, River Mappability, Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.797	.324		14.787	.000
	Water Landmark Identifiability	.263	.092	.365	2.854	.006
2	(Constant)	4.448	.353		12.585	.000
	Water Landmark Identifiability	.305	.091	.423	3.342	.002
	River Mappability	.268	.125	.272	2.152	.036
3	(Constant)	3.955	.397		9.968	.000
	Water Landmark Identifiability	.272	.089	.377	3.065	.003
	River Mappability	.315	.121	.320	2.603	.012
	Canal Mappability	.228	.096	.291	2.378	.021

a. Dependent Variable: Coherence Score 2B

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Water Landmark Mappability	-.197[b]	-1.534	.131	-.208	.963
	Canal Mappability	.239[b]	1.879	.066	.252	.962
	River Mappability	.272[b]	2.152	.036	.286	.954
	Lake Mappability	.089[b]	.691	.492	.095	.998
	Harbour Mappability	-.128[b]	-.927	.358	-.128	.866
	Canal Identitifiability	.041[b]	.315	.754	.044	.995
	River Identitifiability	.231[b]	1.830	.073	.246	.986
	Lake Identifiability	-.036[b]	-.275	.784	-.038	.998
	Harbour Identifiability	-.133[b]	-1.034	.306	-.142	.995
	Water Landmark Attachment	.056[b]	.392	.697	.054	.815
	Canal Attachment	.040[b]	.305	.762	.042	.991
	River Attachment	.086[b]	.668	.507	.092	.987
	Lake Attachment	-.025[b]	-.193	.848	-.027	.993
	Harbour Attachment	-.141[b]	-1.108	.273	-.152	.999

2	Water Landmark Mappability	-.173[c]	-1.376	.175	-.189	.954
	Canal Mappability	.291[c]	2.378	.021	.316	.937
	Lake Mappability	.102[c]	.818	.417	.114	.996
	Harbour Mappability	-.070[c]	-.511	.612	-.071	.827
	Canal Identitifiability	.113[c]	.883	.381	.123	.934
	River Identitifiability	.183[c]	1.454	.152	.200	.944
	Lake Identifiability	.009[c]	.073	.942	.010	.970
	Harbour Identifiability	-.077[c]	-.601	.551	-.084	.946
	Water Landmark Attachment	.068[c]	.489	.627	.068	.813
	Canal Attachment	.078[c]	.616	.541	.086	.972
	River Attachment	-.003[c]	-.022	.982	-.003	.878
	Lake Attachment	.030[c]	.233	.817	.033	.953
	Harbour Attachment	-.083[c]	-.650	.518	-.091	.943
3	Water Landmark Mappability	-.107[d]	-.855	.397	-.120	.894
	Lake Mappability	.073[d]	.611	.544	.086	.985
	Harbour Mappability	.031[d]	.222	.826	.031	.745
	Canal Identitifiability	-.088[d]	-.580	.565	-.082	.613
	River Identitifiability	.131[d]	1.054	.297	.147	.908
	Lake Identifiability	.005[d]	.044	.965	.006	.970
	Harbour Identifiability	-.010[d]	-.076	.940	-.011	.894
	Water Landmark Attachment	.072[d]	.545	.588	.077	.813
	Canal Attachment	-.061[d]	-.449	.655	-.063	.782
	River Attachment	-.024[d]	-.189	.851	-.027	.874
	Lake Attachment	.014[d]	.116	.908	.016	.950
	Harbour Attachment	-.046[d]	-.372	.711	-.053	.927

a. Dependent Variable: Coherence Score 2B
b. Predictors in the Model: (Constant), Water Landmark Identifiability
c. Predictors in the Model: (Constant), Water Landmark Identifiability, River Mappability
d. Predictors in the Model: (Constant), Water Landmark Identifiability, River Mappability, Canal Mappability

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Coherence_2B
  /METHOD=STEPWISE A1_C A1_R B1_M D1_R.
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Water Landmark Identifiability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Aquaphilia Baseline	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Canal Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	River Mappability	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Dual-Perspective Coherence (Coding Scheme 2B)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.379[a]	.143	.126	1.99419
2	.533[b]	.285	.255	1.84137
3	.587[c]	.345	.303	1.78040
4	.636[d]	.404	.352	1.71637

a. Predictors: (Constant), Water Landmark Identifiability

b. Predictors: (Constant), Water Landmark Identifiability, Aquaphilia Baseline

c. Predictors: (Constant), Water Landmark Identifiability, Aquaphilia Baseline, Canal Mappability

d. Predictors: (Constant), Water Landmark Identifiability, Aquaphilia Baseline, Canal Mappability, River Mappability

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	32.618	1	32.618	8.202	.006[b]
	Residual	194.863	49	3.977		
	Total	227.480	50			
2	Regression	64.730	2	32.365	9.545	.000[c]
	Residual	162.751	48	3.391		
	Total	227.480	50			
3	Regression	78.498	3	26.166	8.255	.000[d]
	Residual	148.982	47	3.170		
	Total	227.480	50			
4	Regression	91.968	4	22.992	7.805	.000[e]
	Residual	135.513	46	2.946		
	Total	227.480	50			

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors: (Constant), Water Landmark Identifiability
c. Predictors: (Constant), Water Landmark Identifiability, Aquaphilia Baseline
d. Predictors: (Constant), Water Landmark Identifiability, Aquaphilia Baseline, Canal Mappability
e. Predictors: (Constant), Water Landmark Identifiability, Aquaphilia Baseline, Canal Mappability, River Mappability

Excluded Variablesa

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Canal Mappability	.246[b]	1.867	.068	.260	.958
	River Mappability	.220[b]	1.661	.103	.233	.962
	Aquaphilia Baseline	-.377[b]	-3.077	.003	-.406	.993
2	Canal Mappability	.251[c]	2.084	.043	.291	.958
	River Mappability	.199[c]	1.625	.111	.231	.959
3	River Mappability	.253[d]	2.138	.038	.301	.928

a. Dependent Variable: Average 8-Stage Coherence (8C)
b. Predictors in the Model: (Constant), Water Landmark Identifiability
c. Predictors in the Model: (Constant), Water Landmark Identifiability, Aquaphilia Baseline
d. Predictors in the Model: (Constant), Water Landmark Identifiability, Aquaphilia Baseline, Canal Mappability

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.657	.335		13.909	.000
	Water Landmark Identifiability	.270	.094	.379	2.864	.006
2	(Constant)	6.860	.780		8.798	.000
	Water Landmark Identifiability	.292	.087	.410	3.344	.002
	Aquaphilia Baseline	-1.081	.351	-.377	-3.077	.003
3	(Constant)	6.525	.771		8.464	.000
	Water Landmark Identifiability	.255	.086	.358	2.962	.005
	Aquaphilia Baseline	-1.090	.340	-.380	-3.211	.002
	Canal Mappability	.193	.093	.251	2.084	.043
4	(Constant)	6.084	.771		7.890	.000
	Water Landmark Identifiability	.283	.084	.397	3.365	.002
	Aquaphilia Baseline	-1.052	.328	-.367	-3.210	.002
	Canal Mappability	.228	.091	.297	2.512	.016
	River Mappability	.249	.117	.253	2.138	.038

a. Dependent Variable: Average 8-Stage Coherence (8C)

APPENDIX G

LITTLE'S MISSING COMPLETELY AT RANDOM TEST RESULTS

The Composite SEP Model Variables:
Water-Based Familiarity, Water-Based Comfort, Water-Based Place Identity, Water-Based Place Dependence, Water-Based Place Attachment, Length of Stay

```
        Number of Observed Variables =   6
        Number of Missing Data Patterns =   3

 Summary of Missing Data Patterns (0 = Missing, 1 = Observed)

          Frequency | Pattern | d2j

              1    |  1 1 1 0 0 1 | 1.759307
              3    |  1 1 1 1 1 0 | 7.449280
             26    |  1 1 1 1 1 1 | 0.950342

 Sum of the Number of Observed Variables Across Patterns (Sigma psubj) =    15


      Little's (1988) Chi-Square Test of MCAR

          Chi-Square (d2)      =     10.159
           df (Sigma psubj - p) =          9
             p-value             =     0.338
```

SAS SCRIPT

```
/******************************************************************************************************************/
*                                                                                       *
*  This SAS macro implements the chi-square test for a missing completely at random (MCAR) mechanism, as          *
*  outlined in Little's (1998) JASA article.  Note that the macro requires SAS version 8.2 (or higher) because     *
*  PROC MI is used to obtain ML estimates of the covariance matrix and mean vector.
*                              *
*                                                                                       *
/******************************************************************************************************************/;

%macromcartest;

/* SPECIFY FILE PATH FOR THE INPUT DATA */

%letdatafile=  'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv';


/* SPECIFY INPUT DATA VARIABLE LIST */

%letvarlist = a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17 a18 a19 a20 a21 a22 a23 a24 a25 a26 a27 a28 a29;

/* SPECIFY VARIABLE SET FOR THE MCAR TEST */

%lettestvars = a2 a3 a4 a5 a6 a16;

/* SPECIFY THE MISSING VALUE CODE */

%letmisscode = 9999;

/*******************************/
/* DO NOT ALTER THE CODE BELOW */
/*******************************/

data one;
	infile&datafile ;
	input&varlist;

%letnumvars = %sysfunc(countw(&testvars));

array m[&numvars] &testvars ;
```

```
array r[&numvars] r1 - r&numvars ;

doi = 1 to &numvars;
        if m[i] = &misscode then m[i] = .;
end;
dropi;

doi = 1 to &numvars;
        r[i] = 1;
        if m[i] = .then r[i] = 0;
end;
dropi;

proc sort;
        by r1-r&numvars;

proc mi data = one nimpute = 0noprint;
        var&testvars;
        emoutem = emcov;

prociml;

use one;
read all var {&testvars} into y;
read all var {%doi = 1%to&numvars; r&i%end;} into r;
useemcov;
read all var {&testvars} into em;

mu = em[1,];
sigma = em[2:nrow(em),];

/* ASSIGN AN INDEX VARIABLE DENOTING EACH CASE'S PATTERN */

jcol = j(nrow(y), 1 , 1);

doi = 2 to nrow(y);
        rdiff = r[i,] - r[i - 1,];
        if max(rdiff) = 0& min(rdiff) = 0 then jcol[i,] = jcol[i - 1,];
        elsejcol[i,] = jcol[i - 1,] + 1;
end;

/* NUMBER OF DISTINCT MISSING DATA PATTERNS */

j = max(jcol);

/* PUT THE NUMBER OF CASES IN EACH PATTERN IN A COL VECTOR M */
```

```
/* PUT THE MISSING DATA INDICATORS FOR EACH PATTERN IN A MATRIX
RJ */

m = j(j, 1, 0);
rj = j(j, ncol(r), 0);

doi = 1 to j;
	count = 0;
		do k = 1 to nrow(y);
			ifjcol[k,] = i then do;
				count = count + 1;
			end;
			ifjcol[k,] = i& count = 1 then rj[i,] = r[k,];
			m[i,] = count;
		end;
end;

/* COMPUTE D^2 STATISTIC FOR EACH J PATTERN */

d2j = j(j, 1, 0);

doi = 1 to j;

/* OBSERVED VALUES FOR PATTERN J */

yj = y[loc(jcol = i),loc(rj[i,] = 1)];

/* VARIABLE MEANS FOR PATTERN J */

ybarobsj = yj[+,]/nrow(yj);

/* D = P X Pj MATRIX OF INDICATORS (SEE P. 1199) */

Dj = j(ncol(y), rj[i,+], 0);

count = 1;
do k = 1 to ncol(rj);
	ifrj[i,k] = 1 then do;
		Dj[k, count] = 1;
		count = count + 1;
	end;
end;

/* REDUCE EM ESTIMATES TO CONTAIN OBSERVED ELEMENTS */

muobsj = mu * Dj;
```

```
sigmaobsj = t(Dj) * sigma * Dj;

/* THE CONTRIBUTION TO THE D^2 STATISTIC FOR EACH OF THE J
PATTERNS */

d2j[i,] = m[i,] * (ybarobsj - muobsj) * inv(sigmaobsj) * t(ybarobsj - muobsj);

end;

/* THE D^2 STATISTIC */

d2 = d2j[+,];

/* DF FOR D^2 */

df = rj[+,+] - ncol(rj);
p = 1 - probchi(d2,df);

/* PRINT ANALYSIS RESULTS */

file print;
put"Number of Observed Variables = " (ncol(rj)) 3.0;
put"Number of Missing Data Patterns = " (j) 3.0; put;
put"Summary of Missing Data Patterns (0 = Missing, 1 = Observed)"; put;
put"Frequency | Pattern | d2j"; put;
doi = 1 to nrow(rj);
put (m[i,]) 6.0"    | " @;
do j = 1 to ncol(rj);
put (rj[i,j]) 2.0 @;
end;
put" | " (d2j[i,]) 8.6;
end;
put;
put"Sum of the Number of Observed Variables Across Patterns (Sigma psubj) = "
(rj[+,+]) 5.0; put;
put"Little's (1988) Chi-Square Test of MCAR"; put;
put"Chi-Square (d2)      = " (d2) 10.3;
put"df (Sigma psubj - p) =    " (df) 7.0;
put"p-value              = " (p) 10.3;

%mendmcartest;
%mcartest;

run;
```

SAS LOG

```
1          ;*';*";*/;quit;run;
2          OPTIONS PAGENO=MIN;
3          %LET _CLIENTTASKLABEL='littles_mcar_test for composite model1';
4          %LET _CLIENTPROJECTPATH='C:\Users\Owner\Desktop\Data
Analysis\SAS\Littles MCAR Test for
4        ! Composite Model.egp';
5          %LET _CLIENTPROJECTNAME='Littles MCAR Test for Composite
Model.egp';
6          %LET _SASPROGRAMFILE=;
7
8          ODS _ALL_ CLOSE;
9          OPTIONS DEV=ACTIVEX;
NOTE: Procedures may not support all options or statements for all devices. For details,
see the
documentation for each procedure.
10         GOPTIONS XPIXELS=0 YPIXELS=0;
11         FILENAME EGSR TEMP;
12         ODS tagsets.sasreport12(ID=EGSR) FILE=EGSR STYLE=Analysis
12       !
STYLESHEET=(URL="file:///C:/Program%20Files/SASHome/x86/BIClientStyles/4.2/
Analysis.css")
12       !  NOGTITLE NOGFOOTNOTE GPATH=&sasworklocation
ENCODING=UTF8 options(rolap="on");
NOTE: Writing TAGSETS.SASREPORT12(EGSR) Body file: EGSR
13
14         GOPTIONS ACCESSIBLE;
15
/*************************************************************************
*****************
15       ! **************************/
16         *
16       !                        *
17         *  This SAS macro implements the chi-square test for a missing completely at
random
17       ! (MCAR) mechanism, as            *
18         *  outlined in Little's (1998) JASA article.  Note that the macro requires SAS
version
18       ! 8.2 (or higher) because      *
19         *  PROC MI is used to obtain ML estimates of the covariance matrix and mean
vector.
19       !                        *                                    *
20         *
20       !                        *
```

```
/*****************************************************************************
******************
! ****************************/;

%macro mcartest;

/* SPECIFY FILE PATH FOR THE INPUT DATA */

%let datafile=  'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv';


/* SPECIFY INPUT DATA VARIABLE LIST */

%let varlist = a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17 a18
a19 a20 a21
!  a22 a23 a24 a25 a26 a27 a28 a29;

/* SPECIFY VARIABLE SET FOR THE MCAR TEST */

%let testvars = a2 a3 a4 a5 a6 a16;

/* SPECIFY THE MISSING VALUE CODE */

%let misscode = 9999;
```



```

/********************************/
/* DO NOT ALTER THE CODE BELOW */
/********************************/

data one;
        infile&datafile ;
        input &varlist;

%let numvars = %sysfunc(countw(&testvars));

array m[&numvars] &testvars ;
array r[&numvars] r1 - r&numvars ;

do i = 1 to &numvars;
        if m[i] = &misscode then m[i] = .;
end;
drop i;

```

```
do i = 1 to &numvars;
        r[i] = 1;
        if m[i] = .then r[i] = 0;
end;
drop i;

proc sort;
        by r1-r&numvars;

proc mi data = one nimpute = 0 noprint;
        var&testvars;
        emoutem = emcov;

prociml;

use one;
read all var {&testvars} into y;
read all var {%do i = 1 %to &numvars; r&i %end;} into r;
use emcov;
read all var {&testvars} into em;

mu = em[1,];
sigma = em[2:nrow(em),];

/* ASSIGN AN INDEX VARIABLE DENOTING EACH CASE'S PATTERN */

jcol = j(nrow(y), 1 , 1);

do i = 2 to nrow(y);
        rdiff = r[i,] - r[i - 1,];
        if max(rdiff) = 0 & min(rdiff) = 0 then jcol[i,] = jcol[i - 1,];
        else jcol[i,] = jcol[i - 1,] + 1;
end;

/* NUMBER OF DISTINCT MISSING DATA PATTERNS */
```

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```

j = max(jcol);

/* PUT THE NUMBER OF CASES IN EACH PATTERN IN A COL VECTOR M */
/* PUT THE MISSING DATA INDICATORS FOR EACH PATTERN IN A MATRIX RJ */

 m = j(j, 1, 0);
```

```
rj = j(j, ncol(r), 0);

do i = 1 to j;
	count = 0;
		do k = 1 to nrow(y);
			if jcol[k,] = i then do;
				count = count + 1;
			end;
			if jcol[k,] = i& count = 1 then rj[i,] = r[k,];
			m[i,] = count;
		end;
end;

/* COMPUTE D^2 STATISTIC FOR EACH J PATTERN */

d2j = j(j, 1, 0);

do i = 1 to j;

/* OBSERVED VALUES FOR PATTERN J */

yj = y[loc(jcol = i),loc(rj[i,] = 1)];

/* VARIABLE MEANS FOR PATTERN J */

ybarobsj = yj[+,]/nrow(yj);

/* D = P X Pj MATRIX OF INDICATORS (SEE P. 1199) */

Dj = j(ncol(y), rj[i,+], 0);

count = 1;
do k = 1 to ncol(rj);
	if rj[i,k] = 1 then do;
		Dj[k, count] = 1;
		count = count + 1;
	end;
end;

/* REDUCE EM ESTIMATES TO CONTAIN OBSERVED ELEMENTS */

muobsj = mu * Dj;
sigmaobsj = t(Dj) * sigma * Dj;

/* THE CONTRIBUTION TO THE D^2 STATISTIC FOR EACH OF THE J PATTERNS */
```

```
d2j[i,] = m[i,] * (ybarobsj - muobsj) * inv(sigmaobsj) * t(ybarobsj - muobsj);
```



```

end;

/* THE D^2 STATISTIC */

d2 = d2j[+,];

/* DF FOR D^2 */

df = rj[+,+] - ncol(rj);
p = 1 - probchi(d2,df);

/* PRINT ANALYSIS RESULTS */

file print;
put "Number of Observed Variables = " (ncol(rj)) 3.0;
put "Number of Missing Data Patterns = " (j) 3.0; put;
put "Summary of Missing Data Patterns (0 = Missing, 1 = Observed)"; put;
put "Frequency | Pattern | d2j"; put;
do i = 1 to nrow(rj);
  put (m[i,]) 6.0 "    | " @;
    do j = 1 to ncol(rj);
      put (rj[i,j]) 2.0 @;
  end;
    put " | " (d2j[i,]) 8.6;
end;
put;
put "Sum of the Number of Observed Variables Across Patterns (Sigma psubj) =
" (rj[+,+])
! 5.0; put;
put "Little's (1988) Chi-Square Test of MCAR"; put;
put "Chi-Square (d2)      = " (d2) 10.3;
put "df (Sigma psubj - p) =    " (df) 7.0;
put "p-value              = " (p) 10.3;

%mend mcartest;
%mcartest;
```

NOTE: The infile 'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv' is:
Filename=C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv,
RECFM=V,LRECL=256,File Size (bytes)=9026,
Last Modified=03Oct2014:14:48:02,

Create Time=02Oct2014:13:41:03

NOTE: 60 records were read from the infile 'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv'.
The minimum record length was 103.
The maximum record length was 193.
NOTE: SAS went to a new line when INPUT statement reached past the end of a line.
NOTE: The data set WORK.ONE has 30 observations and 35 variables.
NOTE: DATA statement used (Total process time):
real time 0.00 seconds
cpu time 0.00 seconds

NOTE: There were 30 observations read from the data set WORK.ONE.
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NOTE: The data set WORK.ONE has 30 observations and 35 variables.
NOTE: PROCEDURE SORT used (Total process time):
real time 0.00 seconds
cpu time 0.00 seconds

NOTE: The EM algorithm (MLE) converges in 14 iterations.
NOTE: The data set WORK.EMCOV has 7 observations and 8 variables.
NOTE: PROCEDURE MI used (Total process time):
real time 0.01 seconds
cpu time 0.01 seconds

NOTE: IML Ready

```
run;
```

NOTE: Module MAIN is undefined in IML; cannot be RUN.

```
GOPTIONS NOACCESSIBLE;
%LET _CLIENTTASKLABEL=;
%LET _CLIENTPROJECTPATH=;
%LET _CLIENTPROJECTNAME=;
%LET _SASPROGRAMFILE=;

;*';*";*/;quit;
```

NOTE: Exiting IML.
NOTE: PROCEDURE IML used (Total process time):
real time 0.00 seconds
cpu time 0.01 seconds

```
!            run;

ODS _ALL_ CLOSE;


QUIT; RUN;
```

The Composite SEP Model Variables (Without Length of Stay):
Water-Based Familiarity, Water-Based Comfort, Water-Based Place Identity, Water-Based Place Dependence, Water-Based Place Attachment

```
      Number of Observed Variables =   5
      Number of Missing Data Patterns =   3

Summary of Missing Data Patterns (0 = Missing, 1 = Observed)

          Frequency | Pattern | d2j

              1    |  1 1 1 0 0 | 1.414392
              5    |  1 1 1 1 0 | 0.933336
             24    |  1 1 1 1 1 | 0.290190

Sum of the Number of Observed Variables Across Patterns (Sigma psubj) =    12


     Little's (1988) Chi-Square Test of MCAR

         Chi-Square (d2)      =      2.638
          df (Sigma psubj - p) =          7
           p-value             =      0.916
```

SAS SCRIPT

```
/*****************************************************************************
******************************************/
*                                                                            *
*  This SAS macro implements the chi-square test for a missing completely at random
(MCAR) mechanism, as          *
*  outlined in Little's (1998) JASA article.  Note that the macro requires SAS version 8.2
(or higher) because     *
*  PROC MI is used to obtain ML estimates of the covariance matrix and mean vector.
*                               *
*                                                                            *
/*****************************************************************************
******************************************/;

%macromcartest;

/* SPECIFY FILE PATH FOR THE INPUT DATA */

%letdatafile=  'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv';


/* SPECIFY INPUT DATA VARIABLE LIST */

%letvarlist = a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17 a18 a19 a20
a21 a22 a23 a24 a25 a26 a27 a28 a29;

/* SPECIFY VARIABLE SET FOR THE MCAR TEST */

%lettestvars = a2 a3 a4 a6 a7;

/* SPECIFY THE MISSING VALUE CODE */

%letmisscode = 9999;

/********************************/
/* DO NOT ALTER THE CODE BELOW */
/********************************/

data one;
        infile&datafile ;
        input&varlist;

%letnumvars = %sysfunc(countw(&testvars));

array m[&numvars] &testvars ;
array r[&numvars] r1 - r&numvars ;
```

```
doi = 1 to &numvars;
	if m[i] = &misscode then m[i] = .;
end;
dropi;

doi = 1 to &numvars;
	r[i] = 1;
	if m[i] = .then r[i] = 0;
end;
dropi;

proc sort;
	by r1-r&numvars;

proc mi data = one nimpute = 0noprint;
	var&testvars;
	emoutem = emcov;

prociml;

use one;
read all var {&testvars} into y;
read all var {%doi = 1%to&numvars; r&i%end;} into r;
useemcov;
read all var {&testvars} into em;

mu = em[1,];
sigma = em[2:nrow(em),];

/* ASSIGN AN INDEX VARIABLE DENOTING EACH CASE'S PATTERN */

jcol = j(nrow(y), 1 , 1);

doi = 2 to nrow(y);
	rdiff = r[i,] - r[i - 1,];
	if max(rdiff) = 0& min(rdiff) = 0 then jcol[i,] = jcol[i - 1,];
	elsejcol[i,] = jcol[i - 1,] + 1;
end;

/* NUMBER OF DISTINCT MISSING DATA PATTERNS */

j = max(jcol);

/* PUT THE NUMBER OF CASES IN EACH PATTERN IN A COL VECTOR M */
```

```
/* PUT THE MISSING DATA INDICATORS FOR EACH PATTERN IN A MATRIX
RJ */

m = j(j, 1, 0);
rj = j(j, ncol(r), 0);

doi = 1 to j;
	count = 0;
		do k = 1 to nrow(y);
			ifjcol[k,] = i then do;
				count = count + 1;
			end;
			ifjcol[k,] = i& count = 1 then rj[i,] = r[k,];
			m[i,] = count;
		end;
end;

/* COMPUTE D^2 STATISTIC FOR EACH J PATTERN */

d2j = j(j, 1, 0);

doi = 1 to j;

/* OBSERVED VALUES FOR PATTERN J */

yj = y[loc(jcol = i),loc(rj[i,] = 1)];

/* VARIABLE MEANS FOR PATTERN J */

ybarobsj = yj[+,]/nrow(yj);

/* D = P X Pj MATRIX OF INDICATORS (SEE P. 1199) */

Dj = j(ncol(y), rj[i,+], 0);

count = 1;
do k = 1 to ncol(rj);
	ifrj[i,k] = 1 then do;
		Dj[k, count] = 1;
		count = count + 1;
	end;
end;

/* REDUCE EM ESTIMATES TO CONTAIN OBSERVED ELEMENTS */

muobsj = mu * Dj;
```

```
sigmaobsj = t(Dj) * sigma * Dj;

/* THE CONTRIBUTION TO THE D^2 STATISTIC FOR EACH OF THE J
PATTERNS */

d2j[i,] = m[i,] * (ybarobsj - muobsj) * inv(sigmaobsj) * t(ybarobsj - muobsj);

end;

/* THE D^2 STATISTIC */

d2 = d2j[+,];

/* DF FOR D^2 */

df = rj[+,+] - ncol(rj);
p = 1 - probchi(d2,df);

/* PRINT ANALYSIS RESULTS */

file print;
put"Number of Observed Variables = " (ncol(rj)) 3.0;
put"Number of Missing Data Patterns = " (j) 3.0; put;
put"Summary of Missing Data Patterns (0 = Missing, 1 = Observed)"; put;
put"Frequency | Pattern | d2j"; put;
doi = 1 to nrow(rj);
put (m[i,]) 6.0"    | " @;
do j = 1 to ncol(rj);
put (rj[i,j]) 2.0 @;
end;
put" | " (d2j[i,]) 8.6;
end;
put;
put"Sum of the Number of Observed Variables Across Patterns (Sigma psubj) = "
(rj[+,+]) 5.0; put;
put"Little's (1988) Chi-Square Test of MCAR"; put;
put"Chi-Square (d2)      = " (d2) 10.3;
put"df (Sigma psubj - p) =    " (df) 7.0;
put"p-value              = " (p) 10.3;

%mendmcartest;
%mcartest;

run;

1         ;*';*";*/;quit;run;
```

```
2          OPTIONS PAGENO=MIN;
3          %LET _CLIENTTASKLABEL='littles_mcar_test without length of stay';
4          %LET _CLIENTPROJECTPATH='';
5          %LET _CLIENTPROJECTNAME='';
6          %LET _SASPROGRAMFILE='C:\Users\Owner\Desktop\Data
Analysis\Final\littles_mcar_test
6        ! without length of stay.sas';
7
8          ODS _ALL_ CLOSE;
9          OPTIONS DEV=ACTIVEX;
NOTE: Procedures may not support all options or statements for all devices. For details,
see the
documentation for each procedure.
10         GOPTIONS XPIXELS=0 YPIXELS=0;
11         FILENAME EGSR TEMP;
12         ODS tagsets.sasreport12(ID=EGSR) FILE=EGSR STYLE=Analysis
12       !
STYLESHEET=(URL="file:///C:/Program%20Files/SASHome/x86/BIClientStyles/4.2/
Analysis.css")
12       !  NOGTITLE NOGFOOTNOTE GPATH=&sasworklocation
ENCODING=UTF8 options(rolap="on");
NOTE: Writing TAGSETS.SASREPORT12(EGSR) Body file: EGSR
13
14         GOPTIONS ACCESSIBLE;
15
/*********************************************************************
*****************
15       ! **************************/
16          *
16       !                        *
17          *  This SAS macro implements the chi-square test for a missing completely at
random
17       ! (MCAR) mechanism, as           *
18          *  outlined in Little's (1998) JASA article.  Note that the macro requires SAS
version
18       ! 8.2 (or higher) because     *
19          *  PROC MI is used to obtain ML estimates of the covariance matrix and mean
vector.
19       !                        *                                      *
20          *
20       !                        *
21
/*********************************************************************
*****************
21       ! **************************/;
22
```

```
%macro mcartest;

/* SPECIFY FILE PATH FOR THE INPUT DATA */

%let datafile=  'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv';


/* SPECIFY INPUT DATA VARIABLE LIST */

%let varlist = a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 a13 a14 a15 a16 a17 a18
a19 a20 a21
!  a22 a23 a24 a25 a26 a27 a28 a29;

/* SPECIFY VARIABLE SET FOR THE MCAR TEST */

%let testvars = a2 a3 a4 a6 a7;

/* SPECIFY THE MISSING VALUE CODE */

```



```
%let misscode = 9999;

/*******************************/
/* DO NOT ALTER THE CODE BELOW */
/*******************************/

data one;
        infile&datafile ;
        input &varlist;

%let numvars = %sysfunc(countw(&testvars));

array m[&numvars] &testvars ;
array r[&numvars] r1 - r&numvars ;

do i = 1 to &numvars;
        if m[i] = &misscode then m[i] = .;
end;
drop i;

do i = 1 to &numvars;
        r[i] = 1;
        if m[i] = .then r[i] = 0;
end;
drop i;
```

```
proc sort;
        by r1-r&numvars;

proc mi data = one nimpute = 0 noprint;
        var&testvars;
        emoutem = emcov;

prociml;

use one;
read all var {&testvars} into y;
read all var {%do i = 1 %to &numvars; r&i %end;} into r;
use emcov;
read all var {&testvars} into em;

mu = em[1,];
sigma = em[2:nrow(em),];

/* ASSIGN AN INDEX VARIABLE DENOTING EACH CASE'S PATTERN */

jcol = j(nrow(y), 1 , 1);

do i = 2 to nrow(y);
        rdiff = r[i,] - r[i - 1,];
        if max(rdiff) = 0 & min(rdiff) = 0 then jcol[i,] = jcol[i - 1,];
        else jcol[i,] = jcol[i - 1,] + 1;
end;
```



```
/* NUMBER OF DISTINCT MISSING DATA PATTERNS */

j = max(jcol);

/* PUT THE NUMBER OF CASES IN EACH PATTERN IN A COL VECTOR M */
/* PUT THE MISSING DATA INDICATORS FOR EACH PATTERN IN A MATRIX RJ */

 m = j(j, 1, 0);
 rj = j(j, ncol(r), 0);

 do i = 1 to j;
        count = 0;
                do k = 1 to nrow(y);
```

```
                if jcol[k,] = i then do;
                    count = count + 1;
                end;
                if jcol[k,] = i& count = 1 then rj[i,] = r[k,];
                m[i,] = count;
            end;
    end;

    /* COMPUTE D^2 STATISTIC FOR EACH J PATTERN */

    d2j = j(j, 1, 0);

    do i = 1 to j;

    /* OBSERVED VALUES FOR PATTERN J */

    yj = y[loc(jcol = i),loc(rj[i,] = 1)];

    /* VARIABLE MEANS FOR PATTERN J */

    ybarobsj = yj[+,]/nrow(yj);

    /* D = P X Pj MATRIX OF INDICATORS (SEE P. 1199) */

    Dj = j(ncol(y), rj[i,+], 0);

    count = 1;
    do k = 1 to ncol(rj);
        if rj[i,k] = 1 then do;
            Dj[k, count] = 1;
            count = count + 1;
        end;
    end;

    /* REDUCE EM ESTIMATES TO CONTAIN OBSERVED ELEMENTS */

    muobsj = mu * Dj;
    sigmaobsj = t(Dj) * sigma * Dj;

    /* THE CONTRIBUTION TO THE D^2 STATISTIC FOR EACH OF THE J PATTERNS */

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    d2j[i,] = m[i,] * (ybarobsj - muobsj) * inv(sigmaobsj) * t(ybarobsj - muobsj);

```

```
end;

/* THE D^2 STATISTIC */

d2 = d2j[+,];

/* DF FOR D^2 */

df = rj[+,+] - ncol(rj);
p = 1 - probchi(d2,df);

/* PRINT ANALYSIS RESULTS */

file print;
put "Number of Observed Variables = " (ncol(rj)) 3.0;
put "Number of Missing Data Patterns = " (j) 3.0; put;
put "Summary of Missing Data Patterns (0 = Missing, 1 = Observed)"; put;
put "Frequency | Pattern | d2j"; put;
do i = 1 to nrow(rj);
  put (m[i,]) 6.0 "    | " @;
    do j = 1 to ncol(rj);
      put (rj[i,j]) 2.0 @;
  end;
    put " | " (d2j[i,]) 8.6;
end;
put;
put "Sum of the Number of Observed Variables Across Patterns (Sigma psubj) =
" (rj[+,+])
! 5.0; put;
put "Little's (1988) Chi-Square Test of MCAR"; put;
put "Chi-Square (d2)      = " (d2) 10.3;
put "df (Sigma psubj - p) =    " (df) 7.0;
put "p-value              = " (p) 10.3;

%mend mcartest;
%mcartest;
```

```
NOTE: The infile 'C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv' is:
    Filename=C:\Users\Owner\Desktop\Data Analysis\SAS\WU.csv,
    RECFM=V,LRECL=256,File Size (bytes)=9026,
    Last Modified=03Oct2014:14:48:02,
    Create Time=02Oct2014:13:41:03

NOTE: 60 records were read from the infile 'C:\Users\Owner\Desktop\Data
Analysis\SAS\WU.csv'.
    The minimum record length was 103.
```

```
      The maximum record length was 193.
NOTE: SAS went to a new line when INPUT statement reached past the end of a line.
NOTE: The data set WORK.ONE has 30 observations and 34 variables.
NOTE: DATA statement used (Total process time):
real time           0.00 seconds
cpu time            0.00 seconds


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NOTE: There were 30 observations read from the data set WORK.ONE.
NOTE: The data set WORK.ONE has 30 observations and 34 variables.
NOTE: PROCEDURE SORT used (Total process time):
real time           0.01 seconds
cpu time            0.00 seconds


NOTE: The EM algorithm (MLE) converges in 24 iterations.
NOTE: The data set WORK.EMCOV has 6 observations and 7 variables.
NOTE: PROCEDURE MI used (Total process time):
real time           0.01 seconds
cpu time            0.01 seconds


NOTE: IML Ready
184
185        run;
NOTE: Module MAIN is undefined in IML; cannot be RUN.
186
187
188        GOPTIONS NOACCESSIBLE;
189        %LET _CLIENTTASKLABEL=;
190        %LET _CLIENTPROJECTPATH=;
191        %LET _CLIENTPROJECTNAME=;
192        %LET _SASPROGRAMFILE=;
193
194        ;*';*";*/;quit;
NOTE: Exiting IML.
NOTE: PROCEDURE IML used (Total process time):
real time           0.01 seconds
cpu time            0.00 seconds

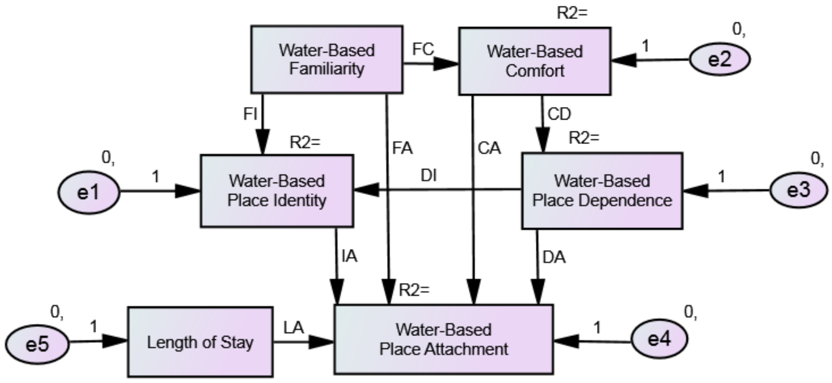
194      !              run;

195        ODS _ALL_ CLOSE;
196
```

```
QUIT; RUN;
```

APPENDIX H

NESTED MODEL TESTING RESULTS FROM AMOS



Path Analysis

C:\Users\Owner\Desktop\Dissertation results\Tripartite Comparison.amw

Analysis Summary

Date and Time

Date: Friday, October 03, 2014
Time: 12:25:02 PM

Title

Tripartite comparison: Friday, October 03, 2014 12:25 PM

Groups

Group number 1 (Group number 1)

Notes for Group (Group number 1)

The model is recursive.
Sample size = 60

Variable Summary (Tripartite Models)

Your model contains the following variables (Tripartite Models)

Observed, endogenous variables
B1U (water-based place identity or identifiability)
D6 (water-based place dependence or orientation)
C0 (water-based place attachment or allocentric aquaphilia)
D8 (water-based comfort)
H5_C (length of stay normalized)
Observed, exogenous variables
A1U (water-based familiarity)
Unobserved, exogenous variables
e1
e3
e4
e2
e5

Variable counts (Tripartite Models)

Number of variables in your model:	11
Number of observed variables:	6
Number of unobserved variables:	5
Number of exogenous variables:	6
Number of endogenous variables:	5

Parameter Summary (Tripartite Models)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	5	0	0	0	0	5
Labeled	9	0	0	0	0	9
Unlabeled	0	0	6	1	5	12
Total	14	0	6	1	5	26

Models

Model 1: Social-Psychological (DI=IA=DA=FI=CD=0) (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Notes for Model (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Computation of degrees of freedom (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	16
Degrees of freedom (27 - 16):	11

Result (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Minimum was achieved
Chi-square = 52.001
Degrees of freedom = 11
Probability level = .000

Tripartite Models (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Estimates (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Scalar Estimates (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.072	0.026	2.709	0.007	FC
D6	<---	D8	0.000				
B1U	<---	D6	0.000				
B1U	<---	A1U	0.000				

			Estimate	S.E.	C.R.	P	Label
C0	<---	D8	0.137	0.596	0.229	0.819	CA
C0	<---	B1U	0.000				
C0	<---	D6	0.000				
C0	<---	A1U	0.290	0.123	2.365	0.018	FA
C0	<---	H5_C	-0.090	0.306	-0.292	0.770	LA

Standardized Regression Weights: (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

			Estimate
D8	<---	A1U	0.340
D6	<---	D8	0.000
B1U	<---	D6	0.000
B1U	<---	A1U	0.000
C0	<---	D8	0.031
C0	<---	B1U	0.000
C0	<---	D6	0.000
C0	<---	A1U	0.311
C0	<---	H5_C	-0.038

Means: (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_6

Intercepts: (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	Estimate	S.E.	C.R.	P	Label
D8	1.705	0.203	8.396	***	par_7
D6	2.105	0.105	20.009	***	par_8
B1U	4.733	0.534	8.863	***	par_9
H5_C	-0.001	0.212	-0.006	0.995	par_10
C0	1.615	1.346	1.200	0.230	par_5

Variances: (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_11
e2	0.622	0.118	5.294	***	par_12
e3	0.620	0.117	5.294	***	par_13
e1	16.829	3.098	5.431	***	par_14
e5	2.441	0.469	5.200	***	par_15
e4	12.375	2.279	5.430	***	par_16

Squared Multiple Correlations: (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	Estimate
D8	.116
D6	.000
H5_C	.000
B1U	.000
C0	.105

Matrices (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Total Effects (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	A1U	D8	D6	H5_C	B1U
D8	0.072	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.300	0.137	0.000	-0.090	0.000

Standardized Total Effects (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	A1U	D8	D6	H5_C	B1U
D8	0.340	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.321	0.031	0.000	-0.038	0.000

Direct Effects (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	A1U	D8	D6	H5_C	B1U
D8	0.072	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.290	0.137	0.000	-0.090	0.000

Standardized Direct Effects (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	A1U	D8	D6	H5_C	B1U
D8	0.340	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000

	A1U	D8	D6	H5_C	B1U
C0	0.311	0.031	0.000	-0.038	0.000

Indirect Effects (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.010	0.000	0.000	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.010	0.000	0.000	0.000	0.000

Minimization History (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Iteration		Negative eigen-values	Condition #	Diameter	F	NTries	Ratio
0	e	0	122.080	9999.000	93.894	0	9999.000
1	e	0	108.718	1.800	77.559	1	0.322
2	e	0	108.894	0.416	56.732	1	1.198
3	e	0	107.552	0.214	52.522	1	1.180
4	e	0	106.413	0.103	52.015	1	1.099
5	e	0	107.043	0.021	52.001	1	1.024
6	e	0	107.117	0.001	52.001	1	1.001

Pairwise Parameter Comparisons (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

Variance-covariance Matrix of Estimates (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	FC	CA	FA	LA	par_5	par_6	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16
FC	0.001															
CA	0.000	0.355														
FA	0.000	-0.025	0.015													
LA	0.000	0.000	0.000	0.094												
par_5	0.000	-0.605	-0.043	0.000	1.811											
par_6	0.000	0.000	0.000	0.000	0.000	0.269										
par_7	-0.005	0.000	0.000	0.000	0.000	0.000	0.041									
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.011								
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.285							
par_10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014			
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	9.600		
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_16	0.000	-0.003	0.000	0.003	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	5.193

Correlations of Estimates (Model 1: Social-Psychological (DI=IA=DA=FI=CD=0))

	FC	CA	FA	LA	par_5	par_6	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16
FC	1.000															
CA	0.000	1.000														
FA	-0.001	-0.348	1.000													
LA	0.000	0.000	0.000	1.000												
par_5	0.001	-0.755	-0.263	0.000	1.000											
par_6	0.000	0.000	0.000	0.000	0.000	1.000										
par_7	-0.855	0.000	0.001	0.000	-0.001	0.000	1.000									
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000								
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000							
par_10	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	1.000						
par_11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000			
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000		
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_16	0.000	-0.002	0.001	0.005	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0) (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Notes for Model (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Computation of degrees of freedom (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	16
Degrees of freedom (27 - 16):	11

Result (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Minimum was achieved
Chi-square = 31.276
Degrees of freedom = 11
Probability level = .001

Tripartite Models (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Estimates (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Scalar Estimates (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.000				
D6	<---	D8	0.000				
B1U	<---	D6	1.903	0.641	2.970	0.003	DI
B1U	<---	A1U	0.000				
C0	<---	D8	0.000				
C0	<---	B1U	0.353	0.101	3.474	***	IA
C0	<---	D6	1.611	0.535	3.013	0.003	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.024	0.258	-0.094	0.925	LA

Standardized Regression Weights: (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

			Estimate
D8	<---	A1U	0.000
D6	<---	D8	0.000
B1U	<---	D6	0.366
B1U	<---	A1U	0.000
C0	<---	D8	0.000
C0	<---	B1U	0.389
C0	<---	D6	0.342
C0	<---	A1U	0.000
C0	<---	H5_C	-0.010

Means: (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_6

Intercepts: (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	Estimate	S.E.	C.R.	P	Label
D8	2.175	0.112	19.383	***	par_7
D6	2.081	0.105	19.862	***	par_8
B1U	0.772	1.424	0.542	0.588	par_9
H5_C	-0.001	0.212	-0.005	0.996	par_10
C0	-1.205	1.105	-1.091	0.275	par_5

Variances: (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_11
e2	0.706	0.133	5.294	***	par_12
e3	0.624	0.118	5.302	***	par_13
e1	14.571	2.698	5.401	***	par_14
e5	2.440	0.469	5.200	***	par_15
e4	8.754	1.623	5.395	***	par_16

Squared Multiple Correlations: (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	Estimate
D8	0.000
D6	0.000
H5_C	0.000
B1U	0.134
C0	0.366

Matrices (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Total Effects (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	1.903	0.000	0.000
C0	0.000	0.000	2.282	-0.024	0.353

Standardized Total Effects (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.366	0.000	0.000
C0	0.000	0.000	0.485	-0.010	0.389

Direct Effects (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	1.903	0.000	0.000
C0	0.000	0.000	1.611	-0.024	0.353

Standardized Direct Effects (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.366	0.000	0.000
C0	0.000	0.000	0.342	-0.010	0.389

Indirect Effects (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.000	0.000	0.671	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.000	0.000	0.143	0.000	0.000

Minimization History (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	323.527	9999.000	87.995	0	9999.000
1	e	0	233.550	1.612	65.534	3	0.000
2	e	0	141.372	0.917	38.763	1	1.063
3	e	0	117.333	0.180	32.590	1	1.215
4	e	0	108.712	0.092	31.372	1	1.154
5	e	0	99.809	0.032	31.277	1	1.063
6	e	0	100.466	0.004	31.276	1	1.007
7	e	0	100.547	0.000	31.276	1	1.000

Pairwise Parameter Comparisons (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

Variance-covariance Matrix of Estimates (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	DI	IA	DA	LA	par_5	par_6	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16
DI	0.410															
IA	-0.001	0.010														
DA	0.001	-0.020	0.286													
LA	0.000	0.000	0.000	0.067												
par_5	0.003	-0.007	-0.500	0.000	1.222											
par_6	0.000	0.000	0.000	0.000	0.000	0.269										
par_7	0.000	0.000	0.000	0.000	0.000	0.000	0.013									
par_8	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.011								
par_9	-0.854	0.002	-0.001	0.000	-0.004	0.000	0.000	-0.001	2.027							
par_10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.018				
par_13	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.014			
par_14	-0.033	0.002	-0.001	0.000	-0.009	0.000	0.000	0.000	0.068	0.000	0.000	0.000	-0.001	7.280		
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_16	0.003	0.001	-0.019	0.001	0.033	0.000	0.000	0.000	-0.006	0.000	0.000	0.000	-0.001	-0.004	0.000	2.633

Correlations of Estimates (Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0))

	DI	IA	DA	LA	par_5	par_6	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16
DI	1.000															
IA	-0.013	1.000														
DA	0.002	-0.371	1.000													
LA	0.000	0.000	0.000	1.000												
par_5	0.004	-0.061	-0.845	0.000	1.000											
par_6	0.000	0.000	0.000	0.000	0.000	1.000										
par_7	0.000	0.000	0.000	0.000	0.000	0.000	1.000									
par_8	0.000	0.000	0.000	0.000	-0.006	0.000	0.000	1.000								
par_9	-0.937	0.012	-0.002	0.000	-0.003	0.000	0.000	-0.005	1.000							
par_10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_13	-0.005	-0.007	-0.003	0.000	0.006	0.000	0.000	0.000	0.005	0.000	0.000	0.000	1.000			
par_14	-0.019	0.008	0.000	0.000	-0.003	0.000	0.000	0.000	0.018	0.000	0.000	0.000	-0.004	1.000		
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_16	0.003	0.008	-0.022	0.002	0.018	0.000	0.000	0.000	-0.003	0.000	0.000	0.000	-0.005	-0.001	0.000	1.000

Model 3: Composite (FA=CA=0) (Model 3: Composite (FA=CA=0))

Notes for Model (Model 3: Composite (FA=CA=0))

Computation of degrees of freedom (Model 3: Composite (FA=CA=0))

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	19
Degrees of freedom (27 - 19):	8

Result (Model 3: Composite (FA=CA=0))

Minimum was achieved
Chi-square = 3.589
Degrees of freedom = 8
Probability level = .892

Tripartite Models (Tripartite Models - Model 3: Composite (FA=CA=0))

Estimates (Tripartite Models - Model 3: Composite (FA=CA=0))

Scalar Estimates (Tripartite Models - Model 3: Composite (FA=CA=0))

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 3: Composite (FA=CA=0))

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.071	0.026	2.691	0.007	FC
D6	<---	D8	0.346	0.117	2.963	0.003	CD
B1U	<---	D6	1.357	0.582	2.333	0.020	DI
B1U	<---	A1U	0.432	0.113	3.810	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.353	0.101	3.498	***	IA
C0	<---	D6	1.606	0.525	3.061	0.002	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.024	0.258	-0.092	0.927	LA

Standardized Regression Weights: (Tripartite Models - Model 3: Composite (FA=CA=0))

			Estimate
D8	<---	A1U	0.338
D6	<---	D8	0.368
B1U	<---	D6	0.265
B1U	<---	A1U	0.425
C0	<---	D8	0.000
C0	<---	B1U	0.388
C0	<---	D6	0.344
C0	<---	A1U	0.000
C0	<---	H5_C	-0.010

Means: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_9

Intercepts: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate	S.E.	C.R.	P	Label
D8	1.702	0.203	8.379	***	par_10
D6	1.331	0.272	4.901	***	par_11
B1U	-0.929	1.412	-0.658	0.510	par_12
H5_C	-0.001	0.212	-0.005	0.996	par_13
C0	-1.200	1.111	-1.080	0.280	par_8

Variances: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_14
e2	0.623	0.118	5.294	***	par_15
e3	0.539	0.102	5.299	***	par_16
e1	11.802	2.181	5.411	***	par_17
e5	2.440	0.469	5.200	***	par_18
e4	8.761	1.624	5.394	***	par_19

Squared Multiple Correlations: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate
D8	0.114
D6	0.135
H5_C	0.000
B1U	0.279
C0	0.354

Matrices (Tripartite Models - Model 3: Composite (FA=CA=0))

Total Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.025	0.346	0.000	0.000	0.000
B1U	0.465	0.470	1.357	0.000	0.000
C0	0.204	0.722	2.086	-0.024	0.353

Standardized Total Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.124	0.368	0.000	0.000	0.000
B1U	0.458	0.097	0.265	0.000	0.000
C0	0.221	0.164	0.447	-0.010	0.388

Direct Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.000	0.346	0.000	0.000	0.000
B1U	0.432	0.000	1.357	0.000	0.000
C0	0.000	0.000	1.606	-0.024	0.353

Standardized Direct Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.000	0.368	0.000	0.000	0.000
B1U	0.425	0.000	0.265	0.000	0.000
C0	0.000	0.000	0.344	-0.010	0.388

Indirect Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.033	0.470	0.000	0.000	0.000
C0	0.204	0.722	0.479	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.124	0.000	0.000	0.000	0.000
B1U	0.033	0.097	0.000	0.000	0.000
C0	0.221	0.164	0.103	0.000	0.000

Minimization History (Model 3: Composite (FA=CA=0))

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	405.617	9999.000	88.734	0	9999.000
1	e	0	157.121	1.854	43.802	3	.000
2	e	0	126.051	.921	10.855	1	1.034
3	e	0	104.748	.195	4.714	1	1.199
4	e	0	91.224	.089	3.661	1	1.144
5	e	0	93.426	.028	3.589	1	1.056
6	e	0	94.272	.003	3.589	1	1.006
7	e	0	94.597	.000	3.589	1	1.000

Pairwise Parameter Comparisons (Model 3: Composite (FA=CA=0))

Variance-covariance Matrix of Estimates (Model 3: Composite (FA=CA=0))

	DI	FC	FI	CD	IA	DA	LA	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18	par_19
DI	0.338																		
FC	0.000	0.001																	
FI	-0.008	0.000	0.013																
CD	0.000	0.000	0.000	0.014															
IA	-0.001	0.000	0.000	0.000	0.010														
DA	0.000	0.000	0.000	0.000	-0.017	0.275													
LA	0.000	0.000	0.000	0.000	0.000	0.000	0.067												
par_8	0.003	0.000	0.000	0.000	-0.013	-0.493	0.000	1.235											
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_10	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.041									
par_11	0.000	0.000	0.000	-0.030	0.000	0.000	0.000	-0.002	0.000	0.000	0.074								
par_12	-0.650	0.000	-0.067	0.001	0.001	-0.001	0.000	-0.004	0.000	-0.001	-0.002	1.994							
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010			
par_17	-0.021	0.000	0.001	0.000	0.001	0.000	0.000	-0.006	0.000	0.000	0.001	0.040	0.000	0.000	0.000	-0.001	4.758		
par_18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_19	0.002	0.000	0.000	0.000	0.001	-0.018	0.001	0.033	0.000	0.000	0.001	-0.005	0.000	0.000	0.000	-0.001	-0.002	0.000	2.638

Correlations of Estimates (Model 3: Composite (FA=CA=0))

	DI	FC	FI	CD	IA	DA	LA	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18	par_19
DI	1.000																		
FC	0.000	1.000																	
FI	-0.126	-0.004	1.000																
CD	-0.002	-0.001	-0.004	1.000															
IA	-0.013	-0.003	0.004	-0.005	1.000														
DA	0.001	0.000	0.000	-0.001	-0.322	1.000													
LA	0.000	0.000	0.000	0.000	0.000	0.000	1.000												
par_8	0.004	0.001	-0.001	0.003	-0.113	-0.845	0.000	1.000											
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_10	0.000	-0.855	0.004	0.001	0.002	0.000	0.000	-0.002	0.000	1.000									
par_11	0.001	0.001	0.003	-0.933	0.004	0.001	0.000	-0.005	0.000	-0.002	1.000								
par_12	-0.791	0.002	-.0419	0.003	0.009	-0.001	0.000	-0.002	0.000	-0.003	-0.004	1.000							
par_13	0.000	0.000	.0000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_14	0.000	0.000	.0000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_15	0.000	0.000	.0000	0.000	-0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_16	-0.003	0.000	.0000	-0.001	-0.004	-0.003	0.000	0.005	0.000	0.000	0.001	0.003	0.000	0.000	0.000	1.000			
par_17	-0.016	0.000	.0002	-0.001	0.006	0.000	0.000	-0.002	0.000	0.000	0.001	0.013	0.000	0.000	0.000	-0.003	1.000		
par_18	0.000	0.000	.0000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_19	0.002	0.000	.0000	-0.002	0.007	-0.022	0.001	0.018	0.000	0.000	0.002	-0.002	0.000	0.000	-0.001	-0.005	-0.001	0.000	1.000

Model 4: Composite without controlling Length of Stay (FA=CA=LA=0) (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Notes for Model (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Computation of degrees of freedom (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Minimum was achieved
Chi-square = 3.596
Degrees of freedom = 9
Probability level = .936

Tripartite Models (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Estimates (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Scalar Estimates (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.071	0.026	2.691	0.007	FC
D6	<---	D8	0.346	0.117	2.963	0.003	CD
B1U	<---	D6	1.358	0.582	2.333	0.020	DI
B1U	<---	A1U	0.432	0.113	3.810	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.354	0.101	3.502	***	IA
C0	<---	D6	1.605	0.525	3.057	0.002	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	0.000				

Standardized Regression Weights: (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

			Estimate
D8	<---	A1U	.338
D6	<---	D8	.368
B1U	<---	D6	.265
B1U	<---	A1U	.425
C0	<---	D8	.000
C0	<---	B1U	.388
C0	<---	D6	.344
C0	<---	A1U	.000
C0	<---	H5_C	.000

Means: (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	Estimate	S.E.	C.R.	P	Label
D8	1.702	0.203	8.379	***	par_9
D6	1.331	0.272	4.901	***	par_10
B1U	-0.930	1.412	-0.658	0.510	par_11
H5_C	0.000	0.212	0.000	1.000	par_12
C0	-1.198	1.112	-1.078	0.281	par_7

Variances: (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.623	0.118	5.294	***	par_14
e3	0.539	0.102	5.299	***	par_15
e1	11.802	2.181	5.411	***	par_16
e5	2.440	0.469	5.200	***	par_17
e4	8.762	1.624	5.394	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	Estimate
D8	0.114
D6	0.135
H5_C	0.000
B1U	0.279
C0	0.354

Matrices (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Total Effects (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.025	0.346	0.000	0.000	0.000
B1U	0.465	0.470	1.358	0.000	0.000
C0	0.204	0.722	2.085	0.000	0.354

Standardized Total Effects (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.124	0.368	0.000	0.000	0.000
B1U	0.458	0.097	0.265	0.000	0.000
C0	0.221	0.164	0.447	0.000	0.388

Direct Effects (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.000	0.346	0.000	0.000	0.000
B1U	0.432	0.000	1.358	0.000	0.000
C0	0.000	0.000	1.605	0.000	0.354

Standardized Direct Effects (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.000	0.368	0.000	0.000	0.000
B1U	0.425	0.000	0.265	0.000	0.000

	A1U	D8	D6	H5_C	B1U
C0	0.000	0.000	0.344	0.000	0.388

Indirect Effects (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.033	0.470	0.000	0.000	0.000
C0	0.204	0.722	0.480	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.124	0.000	0.000	0.000	0.000
B1U	0.033	0.097	0.000	0.000	0.000
C0	0.221	0.164	0.103	0.000	0.000

Minimization History (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	400.458	9999.000	87.873	0	9999.000
1	e	0	155.279	1.836	41.320	3	0.000
2	e	0	118.862	0.896	9.869	1	1.035
3	e	0	104.094	0.189	4.479	1	1.192
4	e	0	96.105	0.083	3.644	1	1.133
5	e	0	92.210	0.023	3.597	1	1.047
6	e	0	95.627	0.002	3.596	1	1.004
7	e	0	95.782	0.000	3.596	1	1.000

Pairwise Parameter Comparisons (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

Variance-covariance Matrix of Estimates (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	DI	FC	FI	CD	IA	DA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	0.338																	
FC	0.000	0.001																
FI	-0.008	0.000	0.013															
CD	0.000	0.000	0.000	0.014														
IA	-0.001	0.000	0.000	0.000	0.010													
DA	0.000	0.000	0.000	0.000	-0.017	0.275												
par_7	0.003	0.000	0.000	0.000	-0.013	-0.493	1.236											
par_8	0.000	.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	.041									
par_10	0.000	0.000	0.000	-0.030	0.000	0.000	-0.002	0.000	.000	.074								
par_11	-0.650	0.000	-0.067	0.001	0.001	-0.001	-0.004	0.000	-.001	-.002	1.995							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010			
par_16	-0.021	0.000	0.001	0.000	0.001	0.000	-0.006	0.000	0.000	0.001	0.040	0.000	0.000	0.000	-0.001	4.758		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.002	0.000	0.000	0.000	0.001	-0.018	0.033	00.000	00.000	0.001	-0.005	0.000	0.000	00.000	-0.001	-0.002	0.000	2.639

Correlations of Estimates (Model 4: Composite without controlling Length of Stay (FA=CA=LA=0))

	DI	FC	FI	CD	IA	DA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	1.000																	
FC	0.000	1.000																
FI	-0.126	-0.004	1.000															
CD	-0.002	-0.001	-0.004	1.000														
IA	-0.013	-0.003	0.004	-0.005	1.000													
DA	0.001	0.000	0.000	-0.001	-0.322	1.000												
par_7	0.004	0.001	-0.001	0.003	-0.113	-0.845	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	0.000	-0.855	0.004	0.001	0.002	0.000	-0.002	0.000	1.000									
par_10	0.001	0.001	0.003	-0.933	0.004	0.001	-0.005	0.000	-0.002	1.000								
par_11	-0.791	0.002	-0.419	0.003	0.009	-0.001	-0.002	0.000	-0.003	-0.004	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	0.000	0.000	0.000	0.000	-0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_15	-0.003	0.000	0.000	-0.001	-0.004	-0.003	0.005	0.000	0.000	0.001	0.003	0.000	0.000	0.000	1.000			
par_16	-0.016	0.000	0.002	-0.001	0.006	0.000	-0.002	0.000	0.000	0.001	0.013	0.000	0.000	0.000	-0.003	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.002	0.000	0.000	-0.002	0.007	-0.022	0.018	0.000	0.000	0.002	-0.002	0.000	0.000	-0.001	-0.005	-0.001	0.000	1.000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	16	52.001	11	0.000	4.727
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	16	31.276	11	0.001	2.843
Model 3: Composite (FA=CA=0)	19	3.589	8	0.892	0.449
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	18	3.596	9	0.936	0.400
Saturated model	27	0.000	0		
Independence model	6	65.563	21	0.000	3.122

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	0.207	-.514	0.249	-0.756	0.080
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	0.523	0.089	0.628	0.131	0.545
Model 3: Composite (FA=CA=0)	0.945	0.856	1.077	1.260	1.000
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	0.945	0.872	1.096	1.283	1.000
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	0.524	0.108	0.042
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	0.524	0.274	0.285
Model 3: Composite (FA=CA=0)	0.381	0.360	0.381
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	0.429	0.405	0.429
Saturated model	0.000	0.000	0.000
Independence model	1.000	0.000	0.000

NCP

Model	NCP	LO 90	HI 90
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	41.001	22.221	67.313
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	20.276	7.245	40.937
Model 3: Composite (FA=CA=0)	0.000	0.000	2.276
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	0.000	0.000	0.715
Saturated model	0.000	0.000	0.000
Independence model	44.563	23.861	72.881

FMIN

Model	FMIN	F0	LO 90	HI 90
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	0.881	0.695	0.377	1.141
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	0.530	0.344	0.123	0.694
Model 3: Composite (FA=CA=0)	0.061	0.000	0.000	0.039
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	0.061	0.000	0.000	0.012
Saturated model	0.000	0.000	0.000	0.000
Independence model	1.111	0.755	0.404	1.235

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	0.251	0.185	0.322	0.000
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	0.177	0.106	0.251	0.004
Model 3: Composite (FA=CA=0)	0.000	0.000	0.069	0.927
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	0.000	0.000	0.037	0.960
Independence model	0.190	0.139	0.243	0.000

AIC

Model	AIC	BCC
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	84.001	88.308
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	63.276	67.583
Model 3: Composite (FA=CA=0)	41.589	46.704
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	39.596	44.443
Saturated model	54.000	61.269
Independence model	77.563	79.178

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	1.424	1.105	1.870	1.497
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	1.072	0.852	1.423	1.145
Model 3: Composite (FA=CA=0)	0.705	0.780	0.818	0.792
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	0.671	0.763	0.775	0.753
Saturated model	0.915	0.915	0.915	1.038
Independence model	1.315	0.964	1.795	1.342

HOELTER

Model	HOELTER .05	HOELTER .01
Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)	23	29
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	38	47
Model 3: Composite (FA=CA=0)	255	331
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	278	356
Independence model	30	36

Nested Model Comparisons

Assuming model Model 3: Composite (FA=CA=0) to be correct:

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)	3	27.687	0.000	0.422	0.481	0.767	1.128
Model 4: Composite without controlling Length of Stay (FA=CA=LA=0)	1	0.008	0.930	0.000	0.000	-0.016	-0.023

Execution time summary

Minimization:	0.000
Miscellaneous:	0.350
Bootstrap:	0.000
Total:	0.350

APPENDIX I

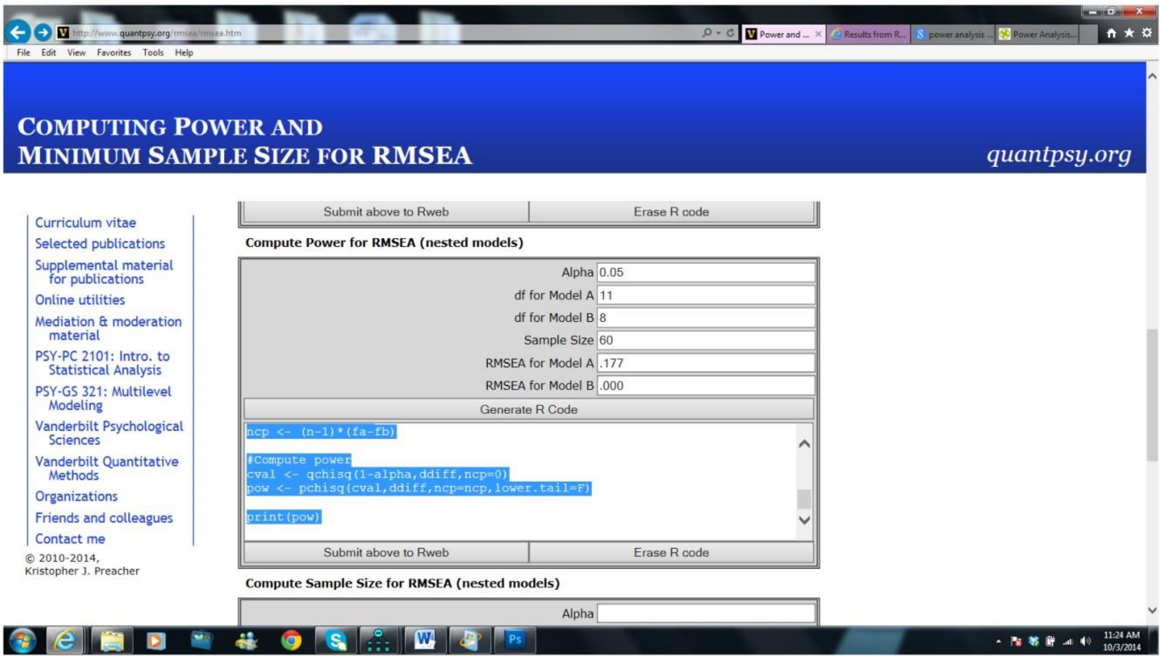
POWER ANALYSIS RESULTS FROM G*POWER 3.1.9.2.

Power Analysis

Preacher, K. J., & Coffman, D. L. (2006, May).Computing power and minimum sample size for RMSEA [Computer software].Available from http://quantpsy.org/.

Model A: Model 2: Environmental-Psychological (FC=CD=FA=CA=FI=0)

Model B: Model 3:Composite (FA=CA=0)



Results from Rweb

You are using Rweb1.03 on the server at rweb.quant.ku.edu

R version 2.13.0 (2011-04-13)
Copyright (C) 2011 The R Foundation for Statistical Computing
ISBN 3-900051-07-0
Platform: x86_64-redhat-linux-gnu (64-bit)

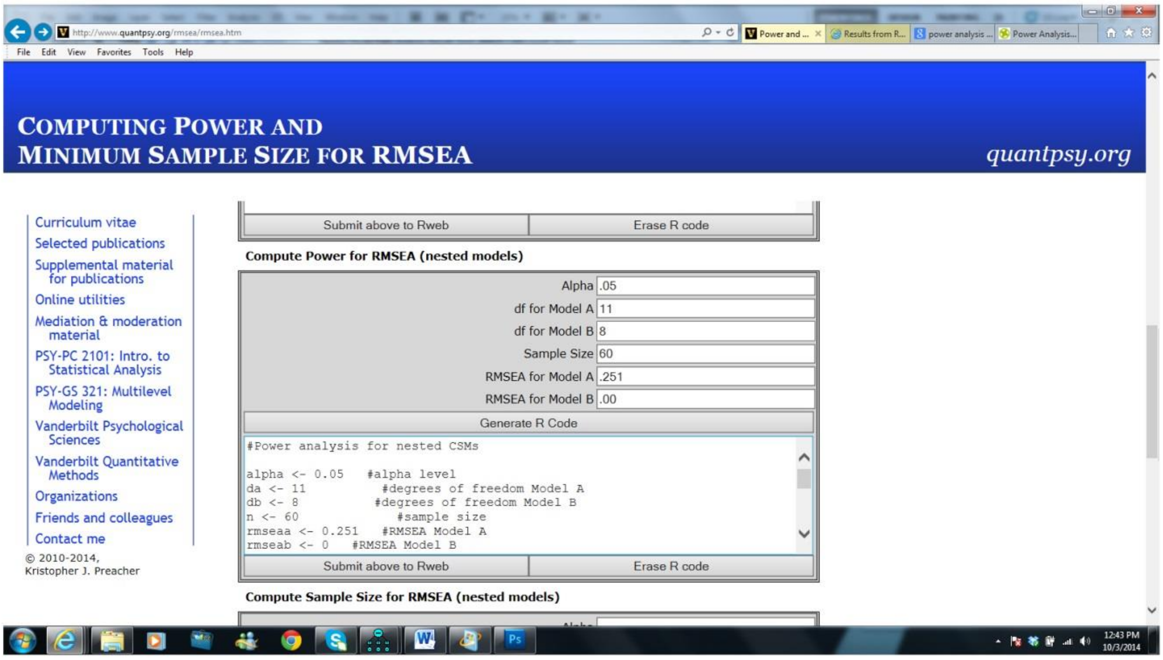
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.

```
Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

Rweb:>png(file= "/tmp/Rout.31156-
90462%03d.png",bg="white",height=800,width=800)
Rweb:>
Rweb:> #Power analysis for nested CSMs
Rweb:>
Rweb:> alpha <- 0.05   #alpha level
Rweb:> da <- 11        #degrees of freedom Model A
Rweb:>db<- 8          #degrees of freedom Model B
Rweb:> n <- 60          #sample size
Rweb:>rmseaa<- 0.177   #RMSEA Model A
Rweb:>rmseab<- 0   #RMSEA Model B
Rweb:>
Rweb:> #Code below need not be changed by user
Rweb:>ddiff<- da-db
Rweb:> fa <- da*rmseaa^2
Rweb:> fb <- db*rmseab^2
Rweb:>ncp<- (n-1)*(fa-fb)
Rweb:>
Rweb:> #Compute power
Rweb:>cval<- qchisq(1-alpha,ddiff,ncp=0)
Rweb:> pow <- pchisq(cval,ddiff,ncp=ncp,lower.tail=F)
Rweb:>
Rweb:> print(pow)
[1] 0.977082
Rweb:>
Rweb:>dev.off()
null device
          1
Rweb:>
```



Model A: Model 1: Social-Psychological (DI=IA=DA=FI=CD=0)

Model B: Model 2: Composite (FA=CA=0)

Results from Rweb

You are using Rweb1.03 on the server at rweb.quant.ku.edu

R version 2.13.0 (2011-04-13)
Copyright (C) 2011 The R Foundation for Statistical Computing
ISBN 3-900051-07-0
Platform: x86_64-redhat-linux-gnu (64-bit)

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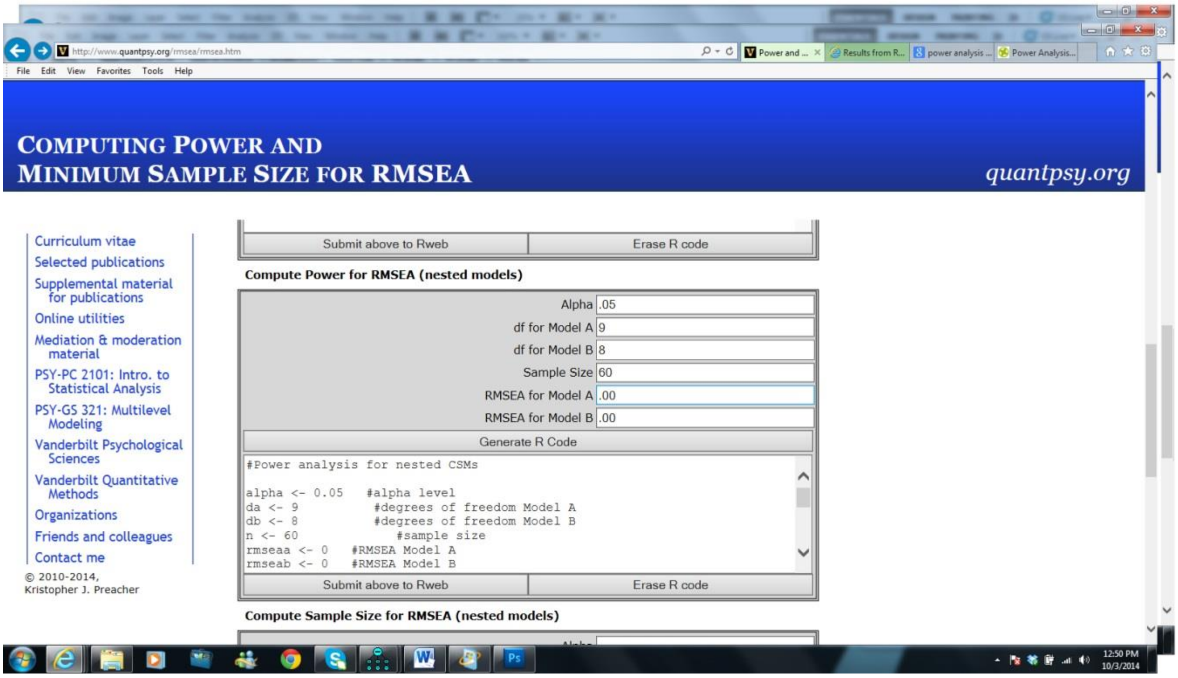
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

```
Rweb:>png(file= "/tmp/Rout.31398-
29974%03d.png",bg="white",height=800,width=800)
Rweb:>
Rweb:> #Power analysis for nested CSMs
Rweb:>
Rweb:> alpha <- 0.05   #alpha level
Rweb:> da <- 11         #degrees of freedom Model A
Rweb:>db<- 8          #degrees of freedom Model B
Rweb:> n <- 60            #sample size
Rweb:>rmseaa<- 0.251   #RMSEA Model A
Rweb:>rmseab<- 0   #RMSEA Model B
Rweb:>
Rweb:> #Code below need not be changed by user
Rweb:>ddiff<- da-db
Rweb:> fa <- da*rmseaa^2
Rweb:> fb <- db*rmseab^2
Rweb:>ncp<- (n-1)*(fa-fb)
Rweb:>
Rweb:> #Compute power
Rweb:>cval<- qchisq(1-alpha,ddiff,ncp=0)
Rweb:> pow <- pchisq(cval,ddiff,ncp=ncp,lower.tail=F)
Rweb:>
Rweb:> print(pow)
[1] 0.9999363
Rweb:>
Rweb:>dev.off()
null device
          1
Rweb:>
```



Model A: Model 1: Composite without Controlling Length of Stay (FA=CA=LA=0)

Model B: Model 2: Composite (FA=CA=0)

Results from Rweb

You are using Rweb1.03 on the server at rweb.quant.ku.edu

R version 2.13.0 (2011-04-13)
Copyright (C) 2011 The R Foundation for Statistical Computing
ISBN 3-900051-07-0
Platform: x86_64-redhat-linux-gnu (64-bit)

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R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or

```
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

Rweb:>png(file= "/tmp/Rout.3144-
43292%03d.png",bg="white",height=800,width=800)
Rweb:>
Rweb:> #Power analysis for nested CSMs
Rweb:>
Rweb:> alpha <- 0.05   #alpha level
Rweb:> da <- 9         #degrees of freedom Model A
Rweb:>db<- 8         #degrees of freedom Model B
Rweb:> n <- 60           #sample size
Rweb:>rmseaa<- 0   #RMSEA Model A
Rweb:>rmseab<- 0   #RMSEA Model B
Rweb:>
Rweb:> #Code below need not be changed by user
Rweb:>ddiff<- da-db
Rweb:> fa <- da*rmseaa^2
Rweb:> fb <- db*rmseab^2
Rweb:>ncp<- (n-1)*(fa-fb)
Rweb:>
Rweb:> #Compute power
Rweb:>cval<- qchisq(1-alpha,ddiff,ncp=0)
Rweb:> pow <- pchisq(cval,ddiff,ncp=ncp,lower.tail=F)
Rweb:>
Rweb:> print(pow)
[1] 0.05
Rweb:>
Rweb:>dev.off()
null device
          1
Rweb:>
```

APPENDIX J

PATH ANALYSIS RESULTS FOR THE COMPOSITE SEP MODEL

C:\Users\Owner\Desktop\Dissertation results\Composite exploratory analysis.amw

Analysis Summary

Date and Time

Date: Friday, October 03, 2014
Time: 1:13:52 PM

Title

Composite exploratory analysis: Friday, October 03, 2014 1:13 PM

Groups

Group number 1 (Group number 1)

Notes for Group (Group number 1)

The model is recursive.
Sample size = 60

Variable Summary (Tripartite Models)

Your model contains the following variables (Tripartite Models)

Observed, endogenous variables
B1U
D6
C0
D8
H5_C
Observed, exogenous variables
A1U
Unobserved, exogenous variables
e1
e3
e4
e2
e5

Variable counts (Tripartite Models)

Number of variables in your model: 11
Number of observed variables: 6

Number of unobserved variables: 5
Number of exogenous variables: 6
Number of endogenous variables: 5

Parameter Summary (Tripartite Models)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	5	0	0	0	0	5
Labeled	9	0	0	0	0	9
Unlabeled	0	0	6	1	5	12
Total	14	0	6	1	5	26

Models

Model 3: Composite (FA=CA=0) (Model 3: Composite (FA=CA=0))

Notes for Model (Model 3: Composite (FA=CA=0))

Computation of degrees of freedom (Model 3: Composite (FA=CA=0))

Number of distinct sample moments: 27
Number of distinct parameters to be estimated: 19
Degrees of freedom (27 - 19): 8

Result (Model 3: Composite (FA=CA=0))

Minimum was achieved
Chi-square = 3.589
Degrees of freedom = 8
Probability level = .892

Tripartite Models (Tripartite Models - Model 3: Composite (FA=CA=0))

Estimates (Tripartite Models - Model 3: Composite (FA=CA=0))

Scalar Estimates (Tripartite Models - Model 3: Composite (FA=CA=0))

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 3: Composite (FA=CA=0))

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.071	0.026	2.691	0.007	FC
D6	<---	D8	0.346	0.117	2.963	0.003	CD
B1U	<---	D6	1.357	0.582	2.333	0.020	DI
B1U	<---	A1U	0.432	0.113	3.810	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.353	0.101	3.498	***	IA
C0	<---	D6	1.606	0.525	3.061	0.002	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.024	0.258	-0.092	0.927	LA

Standardized Regression Weights: (Tripartite Models - Model 3: Composite (FA=CA=0))

			Estimate
D8	<---	A1U	0.338
D6	<---	D8	0.368
B1U	<---	D6	0.265
B1U	<---	A1U	0.425
C0	<---	D8	0.000
C0	<---	B1U	0.388
C0	<---	D6	0.344
C0	<---	A1U	0.000
C0	<---	H5_C	-0.010

Means: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	.519	12.658	***	par_9

Intercepts: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate	S.E.	C.R.	P	Label
D8	1.702	0.203	8.379	***	par_10
D6	1.331	0.272	4.901	***	par_11
B1U	-0.929	1.412	-0.658	0.510	par_12
H5_C	-0.001	0.212	-0.005	0.996	par_13
C0	-1.200	1.111	-1.080	0.280	par_8

Variances: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_14
e2	0.623	0.118	5.294	***	par_15
e3	0.539	0.102	5.299	***	par_16
e1	11.802	2.181	5.411	***	par_17
e5	2.440	0.469	5.200	***	par_18
e4	8.761	1.624	5.394	***	par_19

Squared Multiple Correlations: (Tripartite Models - Model 3: Composite (FA=CA=0))

	Estimate
D8	0.114
D6	0.135
H5_C	0.000
B1U	0.279
C0	0.354

Matrices (Tripartite Models - Model 3: Composite (FA=CA=0))

Total Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.025	0.346	0.000	0.000	0.000
B1U	0.465	0.470	1.357	0.000	0.000
C0	0.204	0.722	2.086	-0.024	0.353

Standardized Total Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.124	0.368	0.000	0.000	0.000
B1U	0.458	0.097	0.265	0.000	0.000
C0	0.221	0.164	0.447	-0.010	0.388

Direct Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.000	0.346	0.000	0.000	0.000
B1U	0.432	0.000	1.357	0.000	0.000
C0	0.000	0.000	1.606	-0.024	0.353

Standardized Direct Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.000	0.368	0.000	0.000	0.000
B1U	0.425	0.000	0.265	0.000	0.000
C0	0.000	0.000	0.344	-0.010	0.388

Indirect Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.033	0.470	0.000	0.000	0.000
C0	0.204	0.722	0.479	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 3: Composite (FA=CA=0))

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.124	0.000	0.000	0.000	0.000
B1U	0.033	0.097	0.000	0.000	0.000
C0	0.221	0.164	0.103	0.000	0.000

Minimization History (Model 3: Composite (FA=CA=0))

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	405.617	9999.000	88.734	0	9999.000
1	e	0	157.121	1.854	43.802	3	0.000
2	e	0	126.051	0.921	10.855	1	1.034
3	e	0	104.748	0.195	4.714	1	1.199
4	e	0	91.224	0.089	3.661	1	1.144
5	e	0	93.426	0.028	3.589	1	1.056
6	e	0	94.272	0.003	3.589	1	1.006
7	e	0	94.597	0.000	3.589	1	1.000

Pairwise Parameter Comparisons (Model 3: Composite (FA=CA=0))

Variance-covariance Matrix of Estimates (Model 3: Composite (FA=CA=0))

	DI	FC	FI	CD	IA	DA	LA	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18	par_19
DI	0.338																		
FC	0.000	0.001																	
FI	-0.008	0.000	0.013																
CD	0.000	0.000	0.000	0.014															
IA	-0.001	0.000	0.000	0.000	0.010														
DA	0.000	0.000	0.000	0.000	-0.017	0.275													
LA	0.000	0.000	0.000	0.000	0.000	0.000	0.067												
par_8	0.003	0.000	0.000	0.000	-0.013	-0.493	0.000	1.235											
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_10	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.041									
par_11	0.000	0.000	0.000	-0.030	0.000	0.000	0.000	-0.002	0.000	0.000	0.074								
par_12	-0.650	0.000	-0.067	0.001	0.001	-0.001	0.000	-0.004	0.000	-0.001	-0.002	1.994							
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010			
par_17	-0.021	0.000	0.001	0.000	0.001	0.000	0.000	-0.006	0.000	0.000	0.001	0.040	0.000	0.000	0.000	-0.001	4.758		
par_18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_19	0.002	0.000	0.000	0.000	0.001	-0.018	0.001	0.033	0.000	0.000	0.001	-0.005	0.000	0.000	0.000	-0.001	-0.002	0.000	2.638

Correlations of Estimates (Model 3: Composite (FA=CA=0))

	DI	FC	FI	CD	IA	DA	LA	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18	par_19
DI	1.000																		
FC	0.000	1.000																	
FI	-0.126	-0.004	1.000																
CD	-0.002	-0.001	-0.004	1.000															
IA	-0.013	-0.003	0.004	-0.005	1.000														
DA	0.001	0.000	0.000	-0.001	-0.322	1.000													
LA	0.000	0.000	0.000	0.000	0.000	0.000	1.000												
par_8	0.004	0.001	-0.001	0.003	-0.113	-0.845	0.000	1.000											
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_10	0.000	-0.855	0.004	0.001	0.002	0.000	0.000	-0.002	0.000	1.000									
par_11	0.001	0.001	0.003	-0.933	0.004	0.001	0.000	-0.005	0.000	-0.002	1.000								
par_12	-0.791	0.002	-0.419	0.003	0.009	-0.001	0.000	-0.002	0.000	-0.003	-0.004	1.000							
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_15	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_16	-0.003	0.000	0.000	-0.001	-0.004	-0.003	0.000	0.005	0.000	0.000	0.001	0.003	0.000	0.000	0.000	1.000			
par_17	-0.016	0.000	0.002	-0.001	0.006	0.000	0.000	-0.002	0.000	0.000	0.001	0.013	0.000	0.000	0.000	-0.003	1.000		
par_18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_19	0.002	0.000	0.000	-0.002	0.007	-0.022	0.001	0.018	0.000	0.000	0.002	-0.002	0.000	0.000	-0.001	-0.005	-0.001	0.000	1.000

Model 5: FA=CA=FI=0 (Model 5: FA=CA=FI=0)

Notes for Model (Model 5: FA=CA=FI=0)

Computation of degrees of freedom (Model 5: FA=CA=FI=0)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 5: FA=CA=FI=0)

Minimum was achieved
Chi-square = 16.040
Degrees of freedom = 9
Probability level = .066

Tripartite Models (Tripartite Models - Model 5: FA=CA=FI=0)

Estimates (Tripartite Models - Model 5: FA=CA=FI=0)

Scalar Estimates (Tripartite Models - Model 5: FA=CA=FI=0)

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 5: FA=CA=FI=0)

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.071	0.026	2.699	0.007	FC
D6	<---	D8	0.346	0.117	2.968	0.003	CD
B1U	<---	D6	1.897	0.641	2.957	0.003	DI
B1U	<---	A1U	0.000				
C0	<---	D8	0.000				
C0	<---	B1U	0.353	0.101	3.481	***	IA
C0	<---	D6	1.611	0.535	3.013	0.003	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.025	0.258	-0.098	0.922	LA

Standardized Regression Weights: (Tripartite Models - Model 5: FA=CA=FI=0)

			Estimate
D8	<---	A1U	0.339
D6	<---	D8	0.368
B1U	<---	D6	0.365
B1U	<---	A1U	0.000
C0	<---	D8	0.000
C0	<---	B1U	0.390
C0	<---	D6	0.342
C0	<---	A1U	0.000
C0	<---	H5_C	-0.011

Means: (Tripartite Models - Model 5: FA=CA=FI=0)

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 5: FA=CA=FI=0)

	Estimate	S.E.	C.R.	P	Label
D8	1.700	0.203	8.375	***	par_9
D6	1.331	0.271	4.907	***	par_10
B1U	0.783	1.426	0.550	0.583	par_11
H5_C	-0.001	0.212	-0.005	0.996	par_12
C0	-1.209	1.106	-1.093	0.274	par_7

Variances: (Tripartite Models - Model 5: FA=CA=FI=0)

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.623	0.118	5.294	***	par_14
e3	0.538	0.102	5.300	***	par_15
e1	14.589	2.701	5.401	***	par_16
e5	2.440	0.469	5.200	***	par_17
e4	8.755	1.623	5.395	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 5: FA=CA=FI=0)

	Estimate
D8	.115
D6	.136
H5_C	.000
B1U	.133
C0	.366

Matrices (Tripartite Models - Model 5: FA=CA=FI=0)

Total Effects (Tripartite Models - Model 5: FA=CA=FI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.025	0.346	0.000	0.000	0.000
B1U	0.047	0.657	1.897	0.000	0.000
C0	0.056	0.790	2.281	-0.025	0.353

Standardized Total Effects (Tripartite Models - Model 5: FA=CA=FI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.339	0.000	0.000	0.000	0.000
D6	0.125	0.368	0.000	0.000	0.000
B1U	0.046	0.134	0.365	0.000	0.000
C0	0.060	0.178	0.484	-0.011	0.390

Direct Effects (Tripartite Models - Model 5: FA=CA=FI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.000	0.346	0.000	0.000	0.000
B1U	0.000	0.000	1.897	0.000	0.000
C0	0.000	0.000	1.611	-0.025	0.353

Standardized Direct Effects (Tripartite Models - Model 5: FA=CA=FI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.339	0.000	0.000	0.000	0.000
D6	0.000	0.368	0.000	0.000	0.000
B1U	0.000	0.000	0.365	0.000	0.000
C0	0.000	0.000	0.342	-0.011	0.390

Indirect Effects (Tripartite Models - Model 5: FA=CA=FI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.047	0.657	0.000	0.000	0.000
C0	0.056	0.790	0.670	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 5: FA=CA=FI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.125	0.000	0.000	0.000	0.000
B1U	0.046	0.134	0.000	0.000	0.000
C0	0.060	0.178	0.142	0.000	0.000

Minimization History (Model 5: FA=CA=FI=0)

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	398.049	9999.000	86.761	0	9999.000
1	e	0	220.409	1.600	52.964	3	0.000
2	e	0	132.550	1.014	22.378	1	1.005
3	e	0	118.382	0.197	16.933	1	1.192
4	e	0	103.778	0.085	16.087	1	1.133
5	e	0	102.247	0.023	16.040	1	1.046
6	e	0	98.906	0.002	16.040	1	1.004
7	e	0	98.575	0.000	16.040	1	1.000

Pairwise Parameter Comparisons (Model 5: FA=CA=FI=0)

Variance-covariance Matrix of Estimates (Model 5: FA=CA=FI=0)

	DI	FC	CD	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	0.411																	
FC	0.000	0.001																
CD	0.000	0.000	0.014															
IA	-0.001	0.000	0.000	0.010														
DA	0.001	0.000	0.000	-0.020	0.286													
LA	0.000	0.000	0.000	0.000	0.000	0.067												
par_7	0.003	0.000	0.000	-0.007	-0.500	0.000	1.224											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.041									
par_10	0.000	0.000	-0.030	0.000	0.000	0.000	-0.001	0.000	0.000	0.074								
par_11	-0.857	0.000	0.000	0.002	-0.001	0.000	-0.004	0.000	0.000	-0.002	2.033							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.010			
par_16	-0.032	0.000	-0.001	0.002	-0.001	0.000	-0.009	0.000	0.000	0.001	0.067	0.000	0.000	0.000	-0.001	7.296		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.003	0.000	0.000	0.001	-0.019	0.001	0.032	0.000	0.000	0.001	-0.006	0.000	0.000	0.000	-0.001	-0.004	0.000	2.633

Correlations of Estimates (Model 5: FA=CA=FI=0)

	DI	FC	CD	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	1.000																	
FC	-0.001	1.000																
CD	-0.003	-0.001	1.000															
IA	-0.013	0.000	-0.003	1.000														
DA	0.002	-0.001	-0.002	-0.370	1.000													
LA	0.000	0.000	0.000	0.000	0.000	1.000												
par_7	0.004	0.001	0.003	-0.062	-0.846	0.000	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	0.001	-0.855	0.001	0.000	0.001	0.000	-0.002	0.000	1.000									
par_10	0.003	0.001	-0.933	0.003	0.002	0.000	-0.005	0.000	-0.002	1.000								
par_11	-0.937	0.001	0.003	0.012	-0.002	0.000	-0.003	0.000	-0.001	-0.004	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	-0.001	0.000	0.000	-0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	1.000				
par_15	-0.005	0.000	-0.001	-0.006	-0.002	0.000	0.005	0.000	0.000	0.001	0.004	0.000	0.000	0.000	1.000			
par_16	-0.019	0.000	-0.002	0.008	0.000	0.000	-0.003	0.000	0.000	0.002	0.017	0.000	0.000	-0.001	-0.004	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.003	0.000	-0.002	0.008	-0.021	0.002	0.018	0.000	0.000	0.002	-0.003	0.000	0.000	-0.001	-0.005	-0.001	0.000	1.000

Model 6: FA=CA=FC=0 (Model 6: FA=CA=FC=0)

Notes for Model (Model 6: FA=CA=FC=0)

Computation of degrees of freedom (Model 6: FA=CA=FC=0)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 6: FA=CA=FC=0)

Minimum was achieved
Chi-square = 10.544
Degrees of freedom = 9
Probability level = .308

Tripartite Models (Tripartite Models - Model 6: FA=CA=FC=0)

Estimates (Tripartite Models - Model 6: FA=CA=FC=0)

Scalar Estimates (Tripartite Models - Model 6: FA=CA=FC=0)

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 6: FA=CA=FC=0)

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.000				
D6	<---	D8	0.349	0.117	2.991	0.003	CD
B1U	<---	D6	1.370	0.576	2.379	0.017	DI
B1U	<---	A1U	0.432	0.112	3.845	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.353	0.101	3.497	***	IA
C0	<---	D6	1.605	0.516	3.110	0.002	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.023	0.258	-0.087	0.930	LA

Standardized Regression Weights: (Tripartite Models - Model 6: FA=CA=FC=0)

			Estimate
D8	<---	A1U	0.000
D6	<---	D8	0.371
B1U	<---	D6	0.272
B1U	<---	A1U	0.432
C0	<---	D8	0.000
C0	<---	B1U	0.385
C0	<---	D6	0.348
C0	<---	A1U	0.000
C0	<---	H5_C	-0.010

Means: (Tripartite Models - Model 6: FA=CA=FC=0)

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 6: FA=CA=FC=0)

	Estimate	S.E.	C.R.	P	Label
D8	2.166	0.112	19.304	***	par_9
D6	1.326	0.271	4.896	***	par_10
B1U	-0.955	1.477	-0.647	0.518	par_11
H5_C	-0.001	0.212	-0.005	0.996	par_12
C0	-1.194	1.118	-1.068	0.285	par_7

Variances: (Tripartite Models - Model 6: FA=CA=FC=0)

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.707	0.134	5.294	***	par_14
e3	0.539	0.102	5.299	***	par_15
e1	11.778	2.177	5.410	***	par_16
e5	2.440	0.469	5.200	***	par_17
e4	8.761	1.624	5.394	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 6: FA=CA=FC=0)

	Estimate
D8	0.000
D6	0.138
H5_C	0.000
B1U	0.260
C0	0.342

Matrices (Tripartite Models - Model 6: FA=CA=FC=0)

Total Effects (Tripartite Models - Model 6: FA=CA=FC=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.349	0.000	0.000	0.000
B1U	0.432	0.478	1.370	0.000	0.000
C0	0.152	0.728	2.089	-0.023	0.353

Standardized Total Effects (Tripartite Models - Model 6: FA=CA=FC=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.371	0.000	0.000	0.000
B1U	0.432	0.101	0.272	0.000	0.000
C0	0.166	0.168	0.452	-0.010	0.385

Direct Effects (Tripartite Models - Model 6: FA=CA=FC=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.349	0.000	0.000	0.000
B1U	0.432	0.000	1.370	0.000	0.000
C0	0.000	0.000	1.605	-0.023	0.353

Standardized Direct Effects (Tripartite Models - Model 6: FA=CA=FC=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.371	0.000	0.000	0.000
B1U	0.432	0.000	0.272	0.000	0.000
C0	0.000	0.000	0.348	-0.010	0.385

Indirect Effects (Tripartite Models - Model 6: FA=CA=FC=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.478	0.000	0.000	0.000
C0	0.152	0.728	0.483	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 6: FA=CA=FC=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.101	0.000	0.000	0.000
C0	0.166	0.168	0.105	0.000	0.000

Minimization History (Model 6: FA=CA=FC=0)

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	413.893	9999.000	90.527	0	9999.000
1	e	0	159.231	1.864	48.884	3	0.000
2	e	0	124.112	0.876	17.967	1	1.056
3	e	0	108.330	0.187	11.760	1	1.206
4	e	0	93.037	0.091	10.627	1	1.149
5	e	0	97.041	0.030	10.545	1	1.060
6	e	0	94.685	0.003	10.544	1	1.007
7	e	0	94.248	0.000	10.544	1	1.000

Pairwise Parameter Comparisons (Model 6: FA=CA=FC=0)
Variance-covariance Matrix of Estimates (Model 6: FA=CA=FC=0)

	DI	FI	CD	IA	DA	LA	par_7	par_8	par_9	par_ 10	par_ 11	par_ 12	par_ 13	par_ 14	par_ 15	par_ 16	par_ 17	par_ 18
DI	0.332																	
FI	0.000	0.013																
CD	0.000	0.000	0.014															
IA	-0.001	0.000	0.000	0.010														
DA	0.000	0.000	0.000	-0.014	0.266													
LA	0.000	0.000	0.000	0.000	0.000	0.067												
par_7	0.003	0.000	0.000	-0.018	-0.487	0.000	1.249											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.013									
par_10	0.000	0.000	-0.029	0.000	0.000	0.000	-0.001	0.000	0.000	0.073								
par_11	-0.690	-0.083	0.000	0.001	0.000	0.000	-0.005	0.000	0.000	-0.001	2.182							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.018				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010			
par_16	-0.021	0.000	0.000	0.001	0.000	0.000	-0.007	0.000	0.000	0.001	0.043	0.000	0.000	0.000	-0.001	4.739		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.002	0.000	-0.001	0.001	-0.018	0.001	0.033	0.000	0.000	0.001	-0.005	0.000	0.000	0.000	-0.001	-0.002	0.000	2.638

Correlations of Estimates (Model 6: FA=CA=FC=0)

	DI	FI	CD	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	1.000																	
FI	0.000	1.000																
CD	-0.002	0.000	1.000															
IA	-0.013	0.002	-0.003	1.000														
DA	0.001	-0.001	-0.002	-0.275	1.000													
LA	0.000	0.000	0.000	0.000	0.000	1.000												
par_7	0.005	0.000	0.003	-0.162	-0.844	0.000	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	0.000	0.000	0.000	0.000	0.000	0.000	-0.002	0.000	1.000									
par_10	0.002	0.000	-0.933	0.002	0.002	0.000	-0.005	0.000	-0.001	1.000								
par_11	-0.812	-0.499	0.002	0.009	0.000	0.000	-0.003	0.000	-0.001	-0.003	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	-0.001	0.000	0.000	-0.001	-0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_15	-0.003	0.000	-0.001	-0.005	-0.003	0.000	0.005	0.000	0.000	0.001	0.003	0.000	0.000	0.000	1.000			
par_16	-0.016	0.000	-0.002	0.006	0.000	0.000	-0.003	0.000	0.000	0.001	0.013	0.000	0.000	0.000	-0.003	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.003	0.000	-0.003	0.006	-0.022	0.001	0.018	0.000	0.000	0.003	-0.002	0.000	0.000	-0.001	-0.005	-0.001	0.000	1.000

Model 7: FA=CA=CD=0 (Model 7: FA=CA=CD=0)

Notes for Model (Model 7: FA=CA=CD=0)

Computation of degrees of freedom (Model 7: FA=CA=CD=0)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 7: FA=CA=CD=0)

Minimum was achieved
Chi-square = 11.704
Degrees of freedom = 9
Probability level = .231

Tripartite Models (Tripartite Models - Model 7: FA=CA=CD=0)

Estimates (Tripartite Models - Model 7: FA=CA=CD=0)

Scalar Estimates (Tripartite Models - Model 7: FA=CA=CD=0)

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 7: FA=CA=CD=0)

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.072	0.026	2.712	0.007	FC
D6	<---	D8	0.000				
B1U	<---	D6	1.370	0.576	2.379	0.017	DI
B1U	<---	A1U	0.432	0.112	3.845	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.353	0.101	3.497	***	IA
C0	<---	D6	1.605	0.516	3.110	0.002	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.023	0.258	-0.087	0.930	LA

Standardized Regression Weights: (Tripartite Models - Model 7: FA=CA=CD=0)

			Estimate
D8	<---	A1U	0.341
D6	<---	D8	0.000
B1U	<---	D6	0.272
B1U	<---	A1U	0.432
C0	<---	D8	0.000
C0	<---	B1U	0.385
C0	<---	D6	0.348
C0	<---	A1U	0.000
C0	<---	H5_C	-0.010

Means: (Tripartite Models - Model 7: FA=CA=CD=0)

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 7: FA=CA=CD=0)

	Estimate	S.E.	C.R.	P	Label
D8	1.706	0.203	8.400	***	par_9
D6	2.081	0.105	19.819	***	par_10
B1U	-0.955	1.477	-0.647	0.518	par_11
H5_C	-0.001	0.212	-0.005	0.996	par_12
C0	-1.194	1.118	-1.068	0.285	par_7

Variances: (Tripartite Models - Model 7: FA=CA=CD=0)

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.622	0.118	5.294	***	par_14
e3	0.625	0.118	5.300	***	par_15
e1	11.778	2.177	5.410	***	par_16
e5	2.440	0.469	5.200	***	par_17
e4	8.761	1.624	5.394	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 7: FA=CA=CD=0)

	Estimate
D8	0.116
D6	0.000
H5_C	0.000
B1U	0.260
C0	0.342

Matrices (Tripartite Models - Model 7: FA=CA=CD=0)

Total Effects (Tripartite Models - Model 7: FA=CA=CD=0)

	A1U	D8	D6	H5_C	B1U
D8	0.072	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.432	0.000	1.370	0.000	0.000
C0	0.152	0.000	2.089	-0.023	0.353

Standardized Total Effects (Tripartite Models - Model 7: FA=CA=CD=0)

	A1U	D8	D6	H5_C	B1U
D8	0.341	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.432	0.000	0.272	0.000	0.000
C0	0.166	0.000	0.452	-0.010	0.385

Direct Effects (Tripartite Models - Model 7: FA=CA=CD=0)

	A1U	D8	D6	H5_C	B1U
D8	0.072	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.432	0.000	1.370	0.000	0.000
C0	0.000	0.000	1.605	-0.023	0.353

Standardized Direct Effects (Tripartite Models - Model 7: FA=CA=CD=0)

	A1U	D8	D6	H5_C	B1U
D8	0.341	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.432	0.000	0.272	0.000	0.000
C0	0.000	0.000	0.348	-0.010	0.385

Indirect Effects (Tripartite Models - Model 7: FA=CA=CD=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.152	0.000	0.483	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 7: FA=CA=CD=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.000	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.166	0.000	0.105	0.000	0.000

Minimization History (Model 7: FA=CA=CD=0)

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	373.616	9999.000	88.116	0	9999.000
1	e	0	168.807	1.886	52.508	3	0.000
2	e	0	129.060	0.846	20.679	1	1.078
3	e	0	110.702	0.186	13.403	1	1.219
4	e	0	96.928	0.097	11.854	1	1.167
5	e	0	93.891	0.038	11.706	1	1.076
6	e	0	91.306	0.005	11.704	1	1.011
7	e	0	91.308	0.000	11.704	1	1.000

Pairwise Parameter Comparisons (Model 7: FA=CA=CD=0)

Variance-covariance Matrix of Estimates (Model 7: FA=CA=CD=0)

	DI	FC	FI	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	0.332																	
FC	0.000	0.001																
FI	0.000	0.000	0.013															
IA	-0.001	0.000	0.000	0.010														
DA	0.000	0.000	0.000	-0.014	0.266													
LA	0.000	0.000	0.000	0.000	0.000	0.067												
par_7	0.003	0.000	0.000	-0.018	-0.487	0.000	1.249											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.041									
par_10	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.011								
par_11	-0.690	0.000	-0.083	0.001	0.000	0.000	-0.005	0.000	0.000	-0.001	2.182							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.014			
par_16	-0.021	0.000	0.000	0.001	0.000	0.000	-0.007	0.000	0.000	0.000	0.043	0.000	0.000	0.000	-0.001	4.739		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.002	0.000	0.000	0.001	-0.018	0.001	0.033	0.000	0.000	0.000	-0.005	0.000	0.000	0.000	-0.001	-0.002	0.000	2.638

Correlations of Estimates (Model 7: FA=CA=CD=0)

	DI	FC	FI	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	1.000																	
FC	0.000	1.000																
FI	0.000	0.000	1.000															
IA	-0.013	0.000	0.002	1.000														
DA	0.001	0.000	-0.001	-0.275	1.000													
LA	0.000	0.000	0.000	0.000	0.000	1.000												
par_7	0.005	0.000	0.000	-0.162	-0.844	0.000	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	0.000	-0.855	0.000	0.000	0.000	0.000	0.000	0.000	1.000									
par_10	0.000	0.000	0.000	0.000	0.000	0.000	-0.006	0.000	0.000	1.000								
par_11	-0.812	0.000	-0.499	0.009	0.000	0.000	-0.003	0.000	0.000	-0.004	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_15	-0.004	0.000	0.000	-0.005	-0.004	0.000	0.006	0.000	0.000	0.000	0.003	0.000	0.000	0.000	1.000			
par_16	-0.016	0.000	0.000	0.006	0.000	0.000	-0.003	0.000	0.000	0.000	0.013	0.000	0.000	0.000	-0.003	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.003	0.000	0.000	0.006	-0.022	0.001	0.018	0.000	0.000	0.000	-0.002	0.000	0.000	0.000	-0.006	-0.001	0.000	1.000

Model 8: FA=CA=DI=0 (Model 8: FA=CA=DI=0)

Notes for Model (Model 8: FA=CA=DI=0)

Computation of degrees of freedom (Model 8: FA=CA=DI=0)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 8: FA=CA=DI=0)

Minimum was achieved
Chi-square = 8.347
Degrees of freedom = 9
Probability level = .500

Tripartite Models (Tripartite Models - Model 8: FA=CA=DI=0)

Estimates (Tripartite Models - Model 8: FA=CA=DI=0)

Scalar Estimates (Tripartite Models - Model 8: FA=CA=DI=0)

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 8: FA=CA=DI=0)

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.072	0.026	2.712	0.007	FC
D6	<---	D8	0.346	0.116	2.970	0.003	CD
B1U	<---	D6	0.000				
B1U	<---	A1U	0.499	0.117	4.253	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.361	0.095	3.811	***	IA
C0	<---	D6	1.562	0.503	3.109	0.002	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.024	0.259	-0.093	0.926	LA

Standardized Regression Weights: (Tripartite Models - Model 8: FA=CA=DI=0)

			Estimate
D8	<---	A1U	0.340
D6	<---	D8	0.369
B1U	<---	D6	0.000
B1U	<---	A1U	0.484
C0	<---	D8	0.000
C0	<---	B1U	0.415
C0	<---	D6	0.344
C0	<---	A1U	0.000
C0	<---	H5_C	-0.011

Means: (Tripartite Models - Model 8: FA=CA=DI=0)

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 8: FA=CA=DI=0)

	Estimate	S.E.	C.R.	P	Label
D8	1.702	0.203	8.387	***	par_9
D6	1.343	0.271	4.960	***	par_10
B1U	1.459	0.901	1.620	0.105	par_11
H5_C	-0.001	0.212	-0.005	0.996	par_12
C0	-1.166	1.184	-0.985	0.325	par_7

Variances: (Tripartite Models - Model 8: FA=CA=DI=0)

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.622	0.118	5.294	***	par_14
e3	.534	0.101	5.296	***	par_15
e1	12.881	2.372	5.431	***	par_16
e5	2.440	0.469	5.200	***	par_17
e4	8.831	1.637	5.394	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 8: FA=CA=DI=0)

	Estimate
D8	0.116
D6	0.136
H5_C	0.000
B1U	0.235
C0	0.308

Matrices (Tripartite Models - Model 8: FA=CA=DI=0)

Total Effects (Tripartite Models - Model 8: FA=CA=DI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.072	0.000	0.000	0.000	0.000
D6	0.025	0.346	0.000	0.000	0.000
B1U	0.499	0.000	0.000	0.000	0.000
C0	0.219	0.540	1.562	-0.024	0.361

Standardized Total Effects (Tripartite Models - Model 8: FA=CA=DI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.340	0.000	0.000	0.000	0.000
D6	0.126	0.369	0.000	0.000	0.000
B1U	0.484	0.000	0.000	0.000	0.000
C0	0.244	0.127	0.344	-0.011	0.415

Direct Effects (Tripartite Models - Model 8: FA=CA=DI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.072	0.000	0.000	0.000	0.000
D6	0.000	0.346	0.000	0.000	0.000
B1U	0.499	0.000	0.000	0.000	0.000
C0	0.000	0.000	1.562	-0.024	0.361

Standardized Direct Effects (Tripartite Models - Model 8: FA=CA=DI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.340	0.000	0.000	0.000	0.000
D6	0.000	0.369	0.000	0.000	0.000
B1U	0.484	0.000	0.000	0.000	0.000
C0	0.000	0.000	0.344	-0.011	0.415

Indirect Effects (Tripartite Models - Model 8: FA=CA=DI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.219	0.540	0.000	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 8: FA=CA=DI=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.126	0.000	0.000	0.000	0.000
B1U	0.000	0.000	0.000	0.000	0.000
C0	0.244	0.127	0.000	0.000	0.000

Minimization History (Model 8: FA=CA=DI=0)

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	370.752	9999.000	82.351	0	9999.000
1	e	0	105.794	1.513	41.481	3	0.000
2	e	0	92.990	0.993	13.034	1	0.973
3	e	0	91.609	0.198	8.813	1	1.166
4	e	0	91.874	00.073	8.360	1	1.099
5	e	0	93.467	00.013	8.347	1	1.025
6	e	0	92.283	.001	8.347	1	1.001

Pairwise Parameter Comparisons (Model 8: FA=CA=DI=0)

Variance-covariance Matrix of Estimates (Model 8: FA=CA=DI=0)

	FC	FI	CD	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
FC	0.001																	
FI	0.000	0.014																
CD	0.000	0.000	0.014															
IA	0.000	0.000	0.000	0.009														
DA	0.000	0.000	0.000	-0.003	0.253													
LA	0.000	0.000	0.000	0.000	0.000	0.067												
par_7	0.000	0.000	0.000	-0.036	-0.515	0.000	1.402											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	-0.005	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.041									
par_10	0.000	0.000	-0.029	0.000	0.000	0.000	-0.002	0.000	0.000	0.073								
par_11	0.000	-0.090	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.811							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010			
par_16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	5.624		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.000	0.000	-0.001	0.000	-0.018	0.001	0.036	0.000	0.000	0.001	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	2.681

Correlations of Estimates (Model 8: FA=CA=DI=0)

	FC	FI	CD	IA	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
FC	1.000																	
FI	0.000	1.000																
CD	-0.001	0.000	1.000															
IA	-0.003	0.000	-0.003	1.000														
DA	-0.001	0.000	-0.002	-0.062	1.000													
LA	0.000	0.000	0.000	0.000	0.000	1.000												
par_7	0.002	0.000	0.003	-0.324	-0.866	0.000	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	-0.855	0.000	0.001	0.003	0.001	0.000	-0.003	0.000	1.000									
par_10	0.001	0.000	-0.933	0.002	0.002	0.000	-0.005	0.000	-0.001	1.000								
par_11	0.000	-0.855	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_13	00.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_15	0.000	0.000	0.000	0.000	-0.003	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000			
par_16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.000	0.000	-0.003	0.001	-0.022	0.001	0.019	0.000	0.000	.003	0.000	0.000	0.000	-0.001	-0.006	0.000	0.000	1.000

Model 9: FA=CA=DA=0 (Model 9: FA=CA=DA=0)

Notes for Model (Model 9: FA=CA=DA=0)

Computation of degrees of freedom (Model 9: FA=CA=DA=0)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 9: FA=CA=DA=0)

Minimum was achieved
Chi-square = 12.073
Degrees of freedom = 9
Probability level = .209

Tripartite Models (Tripartite Models - Model 9: FA=CA=DA=0)

Estimates (Tripartite Models - Model 9: FA=CA=DA=0)

Scalar Estimates (Tripartite Models - Model 9: FA=CA=DA=0)

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 9: FA=CA=DA=0)

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.071	0.026	2.690	0.007	FC
D6	<---	D8	0.345	0.117	2.956	0.003	CD
B1U	<---	D6	1.298	0.587	2.212	0.027	DI
B1U	<---	A1U	0.435	0.114	3.820	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.467	0.102	4.553	***	IA
C0	<---	D6	0.000				
C0	<---	A1U	0.000				
C0	<---	H5_C	0.005	0.277	0.017	0.986	LA

Standardized Regression Weights: (Tripartite Models - Model 9: FA=CA=DA=0)

			Estimate
D8	<---	A1U	0.338
D6	<---	D8	0.367
B1U	<---	D6	0.253
B1U	<---	A1U	0.428
C0	<---	D8	0.000
C0	<---	B1U	0.510
C0	<---	D6	0.000
C0	<---	A1U	0.000
C0	<---	H5_C	0.002

Means: (Tripartite Models - Model 9: FA=CA=DA=0)

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 9: FA=CA=DA=0)

	Estimate	S.E.	C.R.	P	Label
D8	1.705	0.203	8.395	***	par_9
D6	1.342	0.272	40.938	***	par_10
B1U	-.838	1.427	-0.587	0.557	par_11
H5_C	0.000	0.212	0.001	0.999	par_12
C0	1.608	0.638	2.520	0.012	par_7

Variances: (Tripartite Models - Model 9: FA=CA=DA=0)

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.623	0.118	5.294	***	par_14
e3	0.537	0.102	5.295	***	par_15
e1	11.898	2.199	5.410	***	par_16
e5	2.440	0.469	5.200	***	par_17
e4	10.154	1.869	5.431	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 9: FA=CA=DA=0)

	Estimate
D8	0.114
D6	0.135
H5_C	0.000
B1U	0.274
C0	0.260

Matrices (Tripartite Models - Model 9: FA=CA=DA=0)

Total Effects (Tripartite Models - Model 9: FA=CA=DA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.025	0.345	0.000	0.000	0.000
B1U	0.467	0.448	1.298	0.000	0.000
C0	0.218	0.209	0.606	0.005	0.467

Standardized Total Effects (Tripartite Models - Model 9: FA=CA=DA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.124	0.367	0.000	0.000	0.000
B1U	0.459	0.093	0.253	0.000	0.000
C0	0.234	0.047	0.129	0.002	0.510

Direct Effects (Tripartite Models - Model 9: FA=CA=DA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.000	0.345	0.000	0.000	0.000
B1U	0.435	0.000	1.298	0.000	0.000
C0	0.000	0.000	0.000	0.005	0.467

Standardized Direct Effects (Tripartite Models - Model 9: FA=CA=DA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.338	0.000	0.000	0.000	0.000
D6	0.000	0.367	0.000	0.000	0.000
B1U	0.428	0.000	0.253	0.000	0.000
C0	0.000	0.000	0.000	0.002	0.510

Indirect Effects (Tripartite Models - Model 9: FA=CA=DA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.032	0.448	0.000	0.000	0.000
C0	0.218	0.209	0.606	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 9: FA=CA=DA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.124	0.000	0.000	0.000	0.000
B1U	0.031	0.093	0.000	0.000	0.000
C0	0.234	0.047	0.129	0.000	0.000

Minimization History (Model 9: FA=CA=DA=0)

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	246.371	9999.000	85.035	0	9999.000
1	e	0	107.280	2.079	64.614	2	0.000
2	e	0	96.446	0.414	28.956	1	1.241
3	e	0	96.553	0.185	16.694	1	1.253
4	e	0	98.071	0.124	12.844	1	1.218
5	e	0	97.877	0.078	12.116	1	1.139
6	e	0	97.756	0.025	12.074	1	1.045
7	e	0	98.620	0.002	12.073	1	1.004
8	e	0	98.624	0.000	12.073	1	1.000

Pairwise Parameter Comparisons (Model 9: FA=CA=DA=0)

Variance-covariance Matrix of Estimates (Model 9: FA=CA=DA=0)

	DI	FC	FI	CD	IA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	0.345																	
FC	0.000	0.001																
FI	-0.008	0.000	0.013															
CD	0.000	0.000	0.000	0.014														
IA	0.000	0.000	0.000	0.000	0.011													
LA	0.000	0.000	0.000	0.000	0.000	0.077												
par_7	0.000	0.000	0.000	0.000	-0.050	0.000	0.407											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.041									
par_10	0.000	0.000	0.000	-0.030	0.000	0.000	0.000	0.000	0.000	0.074								
par_11	-0.665	0.000	-0.067	0.000	0.000	0.000	0.000	0.000	-0.001	-0.002	20.037							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010			
par_16	-0.023	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.045	0.000	0.000	0.000	-0.001	4.838		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.495

Correlations of Estimates (Model 9: FA=CA=DA=0)

	DI	FC	FI	CD	IA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	1.000																	
FC	0.000	1.000																
FI	-0.127	-0.005	1.000															
CD	-0.001	0.000	-0.004	1.000														
IA	0.000	0.000	0.000	0.000	1.000													
LA	0.000	0.000	0.000	0.000	0.000	1.000												
par_7	0.000	0.000	0.000	0.000	-0.760	0.000	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	0.000	-0.855	0.004	0.000	0.000	0.000	0.000	0.000	1.000									
par_10	0.001	0.000	0.004	-0.933	0.000	0.000	0.000	0.000	-0.001	1.000								
par_11	-0.794	0.003	-0.415	0.003	0.000	0.000	0.000	0.000	-0.003	-0.004	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_15	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	1.000			
par_16	-0.018	0.000	0.002	-0.002	0.000	0.000	0.000	0.000	0.000	0.002	0.014	0.000	0.000	0.000	-0.003	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Model 10: FA=CA=IA=0 (Model 10: FA=CA=IA=0)

Notes for Model (Model 10: FA=CA=IA=0)

Computation of degrees of freedom (Model 10: FA=CA=IA=0)

Number of distinct sample moments:	27
Number of distinct parameters to be estimated:	18
Degrees of freedom (27 - 18):	9

Result (Model 10: FA=CA=IA=0)

Minimum was achieved
Chi-square = 14.541
Degrees of freedom = 9
Probability level = .104

Tripartite Models (Tripartite Models - Model 10: FA=CA=IA=0)

Estimates (Tripartite Models - Model 10: FA=CA=IA=0)

Scalar Estimates (Tripartite Models - Model 10: FA=CA=IA=0)

Maximum Likelihood Estimates

Regression Weights: (Tripartite Models - Model 10: FA=CA=IA=0)

			Estimate	S.E.	C.R.	P	Label
D8	<---	A1U	0.071	0.026	2.684	0.007	FC
D6	<---	D8	0.348	0.117	2.969	0.003	CD
B1U	<---	D6	1.403	0.576	2.436	0.015	DI
B1U	<---	A1U	0.430	0.113	3.810	***	FI
C0	<---	D8	0.000				
C0	<---	B1U	0.000				
C0	<---	D6	2.304	0.539	4.271	***	DA
C0	<---	A1U	0.000				
C0	<---	H5_C	-0.070	0.283	-0.247	0.805	LA

Standardized Regression Weights: (Tripartite Models - Model 10: FA=CA=IA=0)

			Estimate
D8	<---	A1U	0.337
D6	<---	D8	0.368
B1U	<---	D6	0.275
B1U	<---	A1U	0.424
C0	<---	D8	0.000
C0	<---	B1U	0.000
C0	<---	D6	0.492
C0	<---	A1U	0.000
C0	<---	H5_C	-0.029

Means: (Tripartite Models - Model 10: FA=CA=IA=0)

	Estimate	S.E.	C.R.	P	Label
A1U	6.567	0.519	12.658	***	par_8

Intercepts: (Tripartite Models - Model 10: FA=CA=IA=0)

	Estimate	S.E.	C.R.	P	Label
D8	1.700	0.203	8.368	***	par_9
D6	1.320	0.272	4.848	***	par_10
B1U	-1.003	1.398	-0.718	0.473	par_11
H5_C	-0.001	0.212	-0.006	0.996	par_12
C0	-0.963	1.197	-0.805	0.421	par_7

Variances: (Tripartite Models - Model 10: FA=CA=IA=0)

	Estimate	S.E.	C.R.	P	Label
A1U	15.879	2.924	5.431	***	par_13
e2	0.624	0.118	5.294	***	par_14
e3	0.544	0.103	5.303	***	par_15
e1	11.716	2.165	5.411	***	par_16
e5	2.441	0.469	5.200	***	par_17
e4	10.470	1.948	5.376	***	par_18

Squared Multiple Correlations: (Tripartite Models - Model 10: FA=CA=IA=0)

	Estimate
D8	0.114
D6	0.136
H5_C	0.000
B1U	0.284
C0	0.243

Matrices (Tripartite Models - Model 10: FA=CA=IA=0)

Total Effects (Tripartite Models - Model 10: FA=CA=IA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.025	0.348	0.000	0.000	0.000
B1U	0.465	0.489	1.403	0.000	0.000
C0	0.057	0.803	2.304	-0.070	0.000

Standardized Total Effects (Tripartite Models - Model 10: FA=CA=IA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.337	0.000	0.000	0.000	0.000
D6	0.124	0.368	0.000	0.000	0.000
B1U	0.458	0.101	0.275	0.000	0.000
C0	0.061	0.181	0.492	-0.029	0.000

Direct Effects (Tripartite Models - Model 10: FA=CA=IA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.071	0.000	0.000	0.000	0.000
D6	0.000	0.348	0.000	0.000	0.000
B1U	0.430	0.000	1.403	0.000	0.000
C0	0.000	0.000	2.304	-0.070	0.000

Standardized Direct Effects (Tripartite Models - Model 10: FA=CA=IA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.337	0.000	0.000	0.000	0.000
D6	0.000	0.368	0.000	0.000	0.000
B1U	0.424	0.000	0.275	0.000	0.000
C0	0.000	0.000	0.492	-0.029	0.000

Indirect Effects (Tripartite Models - Model 10: FA=CA=IA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.025	0.000	0.000	0.000	0.000
B1U	0.035	0.489	0.000	0.000	0.000
C0	0.057	0.803	0.000	0.000	0.000

Standardized Indirect Effects (Tripartite Models - Model 10: FA=CA=IA=0)

	A1U	D8	D6	H5_C	B1U
D8	0.000	0.000	0.000	0.000	0.000
D6	0.124	0.000	0.000	0.000	0.000
B1U	0.034	0.101	0.000	0.000	0.000
C0	0.061	0.181	0.000	0.000	0.000

Minimization History (Model 10: FA=CA=IA=0)

Iteration		Negative eigenvalues	Condition #	Diameter	F	NTries	Ratio
0	e	0	285.157	9999.000	89.417	0	9999.000
1	e	0	154.163	1.280	40.428	3	0.000
2	e	0	111.376	1.138	16.262	1	0.931
3	e	0	112.408	0.172	14.612	1	1.112
4	e	0	113.235	0.045	14.542	1	1.046
5	e	0	112.967	0.004	14.541	1	1.005
6	e	0	112.967	0.000	14.541	1	1.000

Pairwise Parameter Comparisons (Model 10: FA=CA=IA=0)

Variance-covariance Matrix of Estimates (Model 10: FA=CA=IA=0)

	DI	FC	FI	CD	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	0.332																	
FC	0.000	0.001																
FI	-0.008	0.000	0.013															
CD	0.000	0.000	0.000	0.014														
DA	-0.001	0.000	0.000	0.000	0.291													
LA	0.000	0.000	0.000	0.000	0.000	0.080												
par_7	0.002	0.000	0.000	0.001	-0.604	0.000	1.432											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.269										
par_9	0.000	-0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.041									
par_10	0.000	0.000	0.000	-0.030	0.001	0.000	-0.002	0.000	0.000	0.074								
par_11	-0.634	0.000	-0.067	0.001	0.001	0.000	-0.001	0.000	-0.001	-0.002	1.954							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.547					
par_14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014				
par_15	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.011			
par_16	-0.019	0.000	0.000	0.000	0.003	0.000	-0.005	0.000	0.000	0.001	0.036	0.000	0.000	0.000	-0.001	4.687		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.220	
par_18	0.004	0.000	0.000	-0.001	-0.023	0.002	0.048	0.000	0.000	0.002	-0.008	0.000	0.000	0.000	-0.001	-0.004	0.000	3.794

Correlations of Estimates (Model 10: FA=CA=IA=0)

	DI	FC	FI	CD	DA	LA	par_7	par_8	par_9	par_10	par_11	par_12	par_13	par_14	par_15	par_16	par_17	par_18
DI	1.000																	
FC	0.000	1.000																
FI	-0.126	-0.004	1.000															
CD	-0.002	-0.002	-0.003	1.000														
DA	-0.003	-0.001	0.001	-0.004	1.000													
LA	0.000	0.000	0.000	0.000	0.000	1.000												
par_7	0.003	0.001	-0.001	0.004	-0.935	0.000	1.000											
par_8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000										
par_9	0.000	-0.855	0.003	0.001	0.001	0.000	-0.002	0.000	1.000									
par_10	0.002	0.002	0.003	-0.933	0.004	0.000	-0.006	0.000	-0.002	1.000								
par_11	-0.788	0.002	-0.423	0.004	0.002	0.000	-0.001	0.000	-0.003	-0.005	1.000							
par_12	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	1.000						
par_13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000					
par_14	-0.001	0.000	0.000	0.000	-0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	1.000				
par_15	-0.004	0.000	0.001	-0.002	-0.007	0.000	0.007	0.000	0.000	0.002	0.003	0.000	0.000	0.000	1.000			
par_16	-0.015	0.000	0.002	-0.001	0.002	0.000	-0.002	0.000	0.000	0.001	0.012	0.000	0.000	0.000	-0.002	1.000		
par_17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	
par_18	0.004	0.000	0.000	-0.003	-0.022	0.004	0.021	0.000	0.000	0.003	-0.003	0.000	0.000	-0.001	-0.007	-0.001	0.000	1.000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Model 3: Composite (FA=CA=0)	19	3.589	8	0.892	0.449
Model 5: FA=CA=FI=0	18	16.040	9	0.066	1.782
Model 6: FA=CA=FC=0	18	10.544	9	0.308	1.172
Model 7: FA=CA=CD=0	18	11.704	9	0.231	1.300
Model 8: FA=CA=DI=0	18	8.347	9	0.500	0.927
Model 9: FA=CA=DA=0	18	12.073	9	0.209	1.341
Model 10: FA=CA=IA=0	18	14.541	9	0.104	1.616
Saturated model	27	.000	0		
Independence model	6	65.563	21	0.000	3.122

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Model 3: Composite (FA=CA=0)	0.945	0.856	1.077	1.260	1.000
Model 5: FA=CA=FI=0	0.755	0.429	0.876	0.631	0.842
Model 6: FA=CA=FC=0	0.839	0.625	0.973	0.919	0.965
Model 7: FA=CA=CD=0	0.821	0.583	0.952	0.858	.939
Model 8: FA=CA=DI=0	0.873	0.703	1.012	1.034	1.000
Model 9: FA=CA=DA=0	0.816	0.570	0.946	0.839	0.931
Model 10: FA=CA=IA=0	0.778	0.482	0.902	0.710	0.876
Saturated model	1.000		1.000		1.000
Independence model	0.000	0.000	0.000	0.000	0.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Model 3: Composite (FA=CA=0)	0.381	0.360	0.381
Model 5: FA=CA=FI=0	0.429	0.324	0.361
Model 6: FA=CA=FC=0	0.429	0.360	0.414
Model 7: FA=CA=CD=0	0.429	0.352	0.403
Model 8: FA=CA=DI=0	0.429	0.374	0.429
Model 9: FA=CA=DA=0	0.429	0.350	0.399
Model 10: FA=CA=IA=0	0.429	0.334	0.375
Saturated model	0.000	0.000	0.000
Independence model	1.000	0.000	0.000

NCP

Model	NCP	LO 90	HI 90
Model 3: Composite (FA=CA=0)	0.000	0.000	2.276
Model 5: FA=CA=FI=0	7.040	0.000	22.310
Model 6: FA=CA=FC=0	1.544	0.000	13.919
Model 7: FA=CA=CD=0	2.704	0.000	15.761
Model 8: FA=CA=DI=0	0.000	0.000	10.266
Model 9: FA=CA=DA=0	3.073	0.000	16.339
Model 10: FA=CA=IA=0	5.541	0.000	20.096
Saturated model	0.000	0.000	0.000
Independence model	44.563	23.861	72.881

FMIN

Model	FMIN	F0	LO 90	HI 90
Model 3: Composite (FA=CA=0)	0.061	0.000	0.000	0.039
Model 5: FA=CA=FI=0	0.272	0.119	0.000	0.378
Model 6: FA=CA=FC=0	0.179	0.026	0.000	0.236
Model 7: FA=CA=CD=0	0.198	0.046	0.000	0.267
Model 8: FA=CA=DI=0	0.141	0.000	0.000	0.174
Model 9: FA=CA=DA=0	0.205	0.052	0.000	0.277
Model 10: FA=CA=IA=0	0.246	0.094	0.000	0.341
Saturated model	0.000	0.000	0.000	0.000
Independence model	1.111	0.755	0.404	1.235

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Model 3: Composite (FA=CA=0)	0.000	0.000	0.069	0.927
Model 5: FA=CA=FI=0	0.115	0.000	0.205	0.122
Model 6: FA=CA=FC=0	0.054	0.000	0.162	0.421
Model 7: FA=CA=CD=0	0.071	0.000	0.172	0.335
Model 8: FA=CA=DI=0	0.000	0.000	0.139	0.611
Model 9: FA=CA=DA=0	0.076	0.000	0.175	0.310
Model 10: FA=CA=IA=0	0.102	0.000	0.195	0.177
Independence model	0.190	0.139	0.243	0.000

AIC

Model	AIC	BCC
Model 3: Composite (FA=CA=0)	41.589	46.704
Model 5: FA=CA=FI=0	52.040	56.886
Model 6: FA=CA=FC=0	46.544	51.390
Model 7: FA=CA=CD=0	47.704	52.550
Model 8: FA=CA=DI=0	44.347	49.193
Model 9: FA=CA=DA=0	48.073	52.920
Model 10: FA=CA=IA=0	50.541	55.387
Saturated model	54.000	61.269
Independence model	77.563	79.178

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Model 3: Composite (FA=CA=0)	0.705	0.780	0.818	0.792
Model 5: FA=CA=FI=0	0.882	0.763	1.141	0.964
Model 6: FA=CA=FC=0	0.789	0.763	0.999	0.871
Model 7: FA=CA=CD=0	0.809	0.763	1.030	0.891
Model 8: FA=CA=DI=0	0.752	0.763	0.937	0.834
Model 9: FA=CA=DA=0	0.815	0.763	1.040	0.897
Model 10: FA=CA=IA=0	0.857	0.763	1.103	0.939
Saturated model	0.915	0.915	0.915	1.038
Independence model	1.315	.964	1.795	1.342

HOELTER

Model	HOELTER .05	HOELTER .01
Model 3: Composite (FA=CA=0)	255	331
Model 5: FA=CA=FI=0	63	80
Model 6: FA=CA=FC=0	95	122
Model 7: FA=CA=CD=0	86	110
Model 8: FA=CA=DI=0	120	154
Model 9: FA=CA=DA=0	83	106
Model 10: FA=CA=IA=0	69	88
Independence model	30	36

Nested Model Comparisons

Assuming model Model 3: Composite (FA=CA=0) to be correct:

Model	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho2
Model 5: FA=CA=FI=0	1	12.452	0.000	0.190	0.216	0.427	0.628
Model 6: FA=CA=FC=0	1	6.955	0.008	0.106	0.121	0.232	0.341
Model 7: FA=CA=CD=0	1	8.115	0.004	0.124	0.141	0.273	0.401
Model 8: FA=CA=DI=0	1	4.759	0.029	0.073	0.083	0.153	0.226
Model 9: FA=CA=DA=0	1	8.485	0.004	0.129	0.147	0.286	0.421
Model 10: FA=CA=IA=0	1	10.953	0.001	0.167	0.190	0.374	0.550

Execution time summary

Minimization:	0.000
Miscellaneous:	0.459
Bootstrap:	0.000
Total:	0.459

APPENDIX K

WATER-COHERENT URBANISM MEASURES AND INTERVIEW QUESTIONS

Variable: openness toward storing runoffs

1. Flood-prone cities are considering the following ways to address flooding issues in the public spaces. How likely would you support storing 90% of the stormwater from public roads and properties during storms by…

a. converting auto lanes to 1m deep canals with bike paths
□ Very (3) □ Somewhat (2) □ Not (1)

b. deepening existing canals from 1m to 3m □ Very (3) □ Somewhat (2) □ Not (1)

c. lowering the grounds of plazas and playgrounds □ Very (3) □ Somewhat (2) □ Not (1)

d. retrofitting plazas to float on top of water □ Very (3) □ Somewhat (2) □ Not (1)

e. retrofitting underground parking for storage □ Very (3) □ Somewhat (2) □ Not (1)

f. building big underground pipes for storage □ Very (3) □ Somewhat (2) □ Not (1)

g. Please specify or explain why you did not support any of the above solutions________

Variable: openness toward infiltrating runoffs

2. How likely would you support returning 90% of the stormwater from public roads and properties after storms by…

a. converting auto lanes to creeks with bike paths □ Very (3) □ Somewhat (2) □ Not (1)

b. converting parking lots into parks □ Very (3) □ Somewhat (2) □ Not (1)

c. converting plazas into parks □ Very (3) □ Somewhat (2) □ Not (1)

d. making roads porous □ Very (3) □ Somewhat (2) □ Not (1)

e. Please specify or explain why you did not support any of the above solutions________

Variable: openness toward water transportation

3. How likely would you travel by water more…

a. if you had an amphibious car? □ Very (3) □ Somewhat (2) □ Not (1)

b. if water were near your home? □ Very (3) □ Somewhat (2) □ Not (1)

c. if water were near where you typically go? □ Very (3) □ Somewhat (2) □ Not (1)

d. if you could take your bicycle along? □ Very (3) □ Somewhat (2) □ Not (1)

e. if the water network were expanded? □ Very (3) □ Somewhat (2) □ Not (1)

f. if water movement generated energy?	□ Very (3) □ Somewhat (2) □ Not (1)
g. if it improved water quality?	□ Very (3) □ Somewhat (2) □ Not (1)
h. if there were more security docking?	□ Very (3) □ Somewhat (2) □ Not (1)
i. if it improved your wellbeing?	□ Very (3) □ Somewhat (2) □ Not (1)
j. if flood evacuation were likely in your area?	□ Very (3) □ Somewhat (2) □ Not (1)
k. if there were no fuel cost?	□ Very (3) □ Somewhat (2) □ Not (1)
l. if it reduced climate change impacts?	□ Very (3) □ Somewhat (2) □ Not (1)
m. if it decreased sea level rise?	□ Very (3) □ Somewhat (2) □ Not (1)
n. if it reduced risks of flooding in your city?	□ Very (3) □ Somewhat (2) □ Not (1)
o. if it reduced risks of flooding in other cities?	□ Very (3) □ Somewhat (2) □ Not (1)
Variable: openness toward canals and creeks	
4. Would you like to see more canals or creeks…	
a. supported floating parks?	□ Very (3) □ Somewhat (2) □ Not (1)
b. supported floating greenhouses?	□ Very (3) □ Somewhat (2) □ Not (1)
c. generated renewable energy?	□ Very (3) □ Somewhat (2) □ Not (1)
d. supplied clean water?	□ Very (3) □ Somewhat (2) □ Not (1)
e. reduced floods?	□ Very (3) □ Somewhat (2) □ Not (1)
f. supported water transportation?	□ Very (3) □ Somewhat (2) □ Not (1)
g. improved water quality?	□ Very (3) □ Somewhat (2) □ Not (1)
h. supported floating bicycle paths?	□ Very (3) □ Somewhat (2) □ Not (1)
i. supported floating traffic lanes?	□ Very (3) □ Somewhat (2) □ Not (1)
j. supported boathouses?	□ Very (3) □ Somewhat (2) □ Not (1)
k. reduced heat in urban areas?	□ Very (3) □ Somewhat (2) □ Not (1)
l. if it reduced climate change impacts?	□ Very (3) □ Somewhat (2) □ Not (1)
m.if it decreased sea level rise?	□ Very (3) □ Somewhat (2) □ Not (1)
n. provided water during droughts?	□ Very (3) □ Somewhat (2) □ Not (1)
o. supported vegetation?	□ Very (3) □ Somewhat (2) □ Not (1)
a. were necessary for distributing water?	□ Very (3) □ Somewhat (2) □ Not (1)
b. were necessary for distributing energy?	□ Very (3) □ Somewhat (2) □ Not (1)
c. were necessary for distributing food?	□ Very (3) □ Somewhat (2) □ Not (1)
d. supported wildlife?	□ Very (3) □ Somewhat (2) □ Not (1)

e. returned stormwater to the ground?	□ Very (3) □ Somewhat (2) □ Not (1)
f. supported floating parks?	□ Very (3) □ Somewhat (2) □ Not (1)
g. were more straight?	□ Very (3) □ Somewhat (2) □ Not (1)
h. were more meandering?	□ Very (3) □ Somewhat (2) □ Not (1)
i. needed energy to keep water in it?	□ Very (3) □ Somewhat (2) □ Not (1)

c. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses. Use the average score across all responses to create variable measure.

APPENDIX L

SKETCH MAP EVALUATION RUBRIC AND CODING SCHEME

Type	Score	Description
Declarative Component	1	Show an impressionist sketch of landmark/node characteristics.
Declarative Relations	2	Illustrate randomly distributed landmarks/nodes unconnected by paths.
Procedural Component	3	Display landmarks/nodes as destinations connected by paths yet with little information about pure path intersections or wayside landmarks.
Procedural Relations	4	Exhibit path segments without wayside landmarks but with some pure path intersections that seem to have been drawn from turn-by-turn instructions.
Hierarchical Component	5	Reveal landmarks/nodes in proximity to major paths, landmark, or nodes without enough pure path intersections to enable shortcut-taking.
Hierarchical Relations	6	Reveal landmarks/nodes in proximity to major paths, landmarks, nodes with enough pure path intersections to enable shortcut-taking.
Topological Component	7	Delineate districts by continuous edges or the clustering of landmarks/nodes.
Topological Relations	8	Show a nested hierarchy of multiple districts delineated based on continuous edges or the clustering of landmarks/nodes.
Configurational Component	7	Indicate a distinct form that resembles only a small part of the city center.

Configurational Relations	8	Capture the entire city structure as one single configuration or a collective pattern greater than the sum of multiple distinct forms.
Projective Component	7	Conjecture abstract components from known topological or configurational components instead of district-defining edges on the ground.
Projective Relations	8	Infer abstract relationships from known topological or configurational relationships instead of actual physical relationships between districts.

c. Code 1 or 0 for indicating correct or incorrect city identification.
d. Assume response categories as equally spaced points along a Likert scale to generate scores as shown above in parentheses.

APPENDIX M

INTERNAL CONSISTENCY TEST AND PRINCIPAL COMPONENTS

ANALYSIS RESULTS FOR THE MEASURES OF AQUAPHILIC URBANISM

```
RELIABILITY
  /VARIABLES=A1U_C B1U_C D6_C D8_C
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	58	96.7
	Excluded[a]	2	3.3
	Total	60	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.705	4

```
FACTOR
  /VARIABLES A1U_C B1U_C D6_C D8_C
  /MISSING MEANSUB
  /ANALYSIS A1U_C B1U_C D6_C D8_C
  /PRINT CORRELATION REPR EXTRACTION ROTATION FSCORE
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(2) ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
  /ROTATION PROMAX(4)
  /SAVE REG(ALL)
  /METHOD=CORRELATION.
```

Factor Analysis

Correlation Matrix[a]

		Water-Based Familiarity	Water-Based Place Identity	Water-Based Place Dependence	Water-Based Comfort
Correlation	Water-Based Familiarity	1.000	.506	.264	.264
	Water-Based Place Identity	.506	1.000	.368	.368
	Water-Based Place Dependence	.264	.368	1.000	1.000
	Water-Based Comfort	.264	.368	1.000	1.000

a. This matrix is not positive definite.

Component Matrix[a]

	Component	
	1	2
Water-Based Familiarity	.571	.680
Water-Based Place Identity	.669	.534
Water-Based Place Dependence	.912	-.408
Water-Based Comfort	.912	-.408

Extraction Method: Principal Component Analysis.
a. 2 components extracted.

Communalities

	Extraction
Water-Based Familiarity	.787
Water-Based Place Identity	.732
Water-Based Place Dependence	.998
Water-Based Comfort	.998

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total
1	2.435	60.880	60.880	2.209
2	1.080	27.008	87.888	1.759

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Reproduced Correlations

		Water-Based Familiarity	Water-Based Place Identity	Water-Based Place Dependence	Water-Based Comfort
Reproduced Correlation	Water-Based Familiarity	.787[a]	.744	.243	.243
	Water-Based Place Identity	.744	.732[a]	.392	.392
	Water-Based Place Dependence	.243	.392	.998[a]	.998
	Water-Based Comfort	.243	.392	.998	.998[a]
Residual[b]	Water-Based Familiarity		-.239	.021	.021
	Water-Based Place Identity	-.239		-.024	-.024
	Water-Based Place Dependence	.021	-.024		.002
	Water-Based Comfort	.021	-.024	.002	

Extraction Method: Principal Component Analysis.
a. Reproduced communalities
b. Residuals are computed between observed and reproduced correlations. There are 1 (16.0%) nonredundant residuals with absolute values greater than 0.05.

Pattern Matrix[a]

	Component	
	1	2
Water-Based Familiarity	-.084	.914
Water-Based Place Identity	.102	.814
Water-Based Place Dependence	.999	-.001
Water-Based Comfort	.999	-.001

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.[a]
a. Rotation converged in 3 iterations.

Structure Matrix

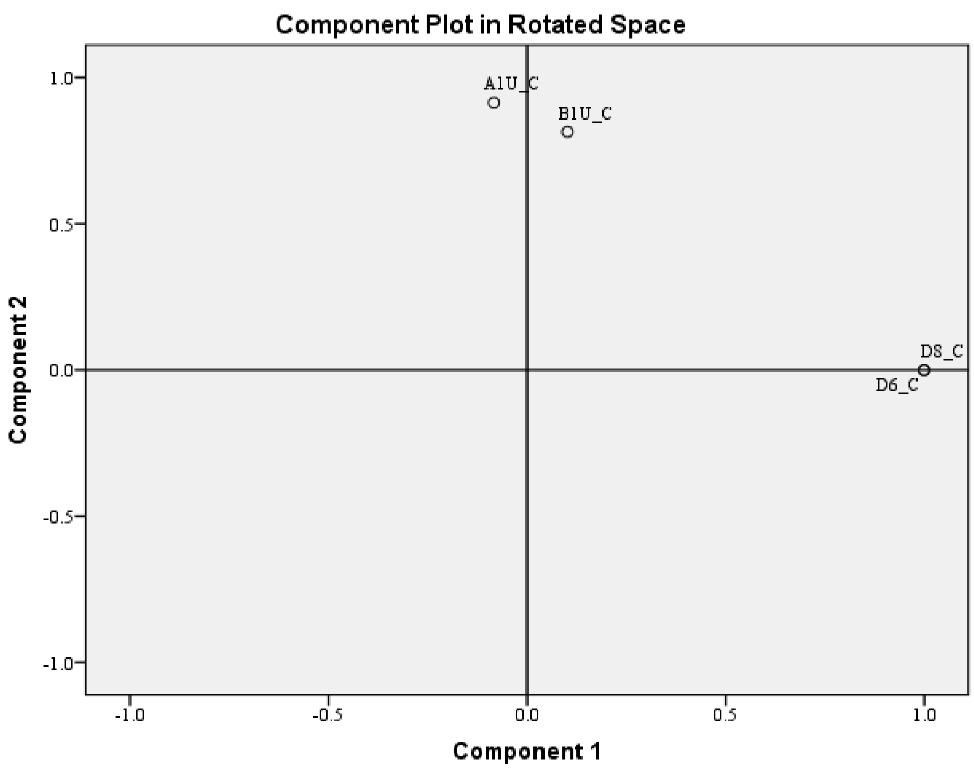
	Component	
	1	2
Water-Based Familiarity	.243	.884
Water-Based Place Identity	.393	.850
Water-Based Place Dependence	.999	.357
Water-Based Comfort	.999	.357

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

Component Correlation Matrix

Component	1	2
1	1.000	.358
2	.358	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.



Component Score Coefficient Matrix

	Component	
	1	2
Water-Based Familiarity	-.043	.610
Water-Based Place Identity	.049	.543
Water-Based Place Dependence	.496	-.002
Water-Based Comfort	.496	-.002

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
Component Scores.

Component Score Covariance Matrix

Component	1	2
1	1.128	.715
2	.715	1.128

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
Component Scores.

APPENDIX N

INTERNAL CONSISTENCY TEST AND PRINCIPAL COMPONENTS ANALYSIS RESULTS FOR THE MEASURES OF THE OPENNESS TOWARD WATER-COHERENT URBANISM

```
RELIABILITY
  /VARIABLES=F3_R_C F4_R_C G1_R_C G2_R_C
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	42	70.0
	Excluded[a]	18	30.0
	Total	60	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.859	4

```
FACTOR
  /VARIABLES F3_R_C F4_R_C G1_R_C G2_R_C
  /MISSING MEANSUB
  /ANALYSIS F3_R_C F4_R_C G1_R_C G2_R_C
  /PRINT UNIVARIATE INITIAL CORRELATION REPR EXTRACTION
ROTATION FSCORE
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1) ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
  /ROTATION PROMAX(4)
  /SAVE REG(ALL)
  /METHOD=CORRELATION.
```

Factor Analysis

Descriptive Statistics

	Mean	Std. Deviation[a]	Analysis N[a]	Missing N
Openness to Storing Public Runoffs	.0000	.27989	50	2
Openness to Infiltrating Public Runoffs	.0000	.30735	50	1
Openness to Water Transportation	.0000	.24915	50	2
Openness to Canals and Creeks	.0000	.18379	50	5

a. For each variable, missing values are replaced with the variable mean.

Correlation Matrix

		Openness to Storing Public Runoffs	Openness to Infiltrating Public Runoffs	Openness to Water Transportation	Openness to Canals and Creeks
Correlation	Openness to Storing Public Runoffs	1.000	.710	.540	.493
	Openness to Infiltrating Public Runoffs	.710	1.000	.542	.487
	Openness to Water Transportation	.540	.542	1.000	.857
	Openness to Canals and Creeks	.493	.487	.857	1.000

Communalities

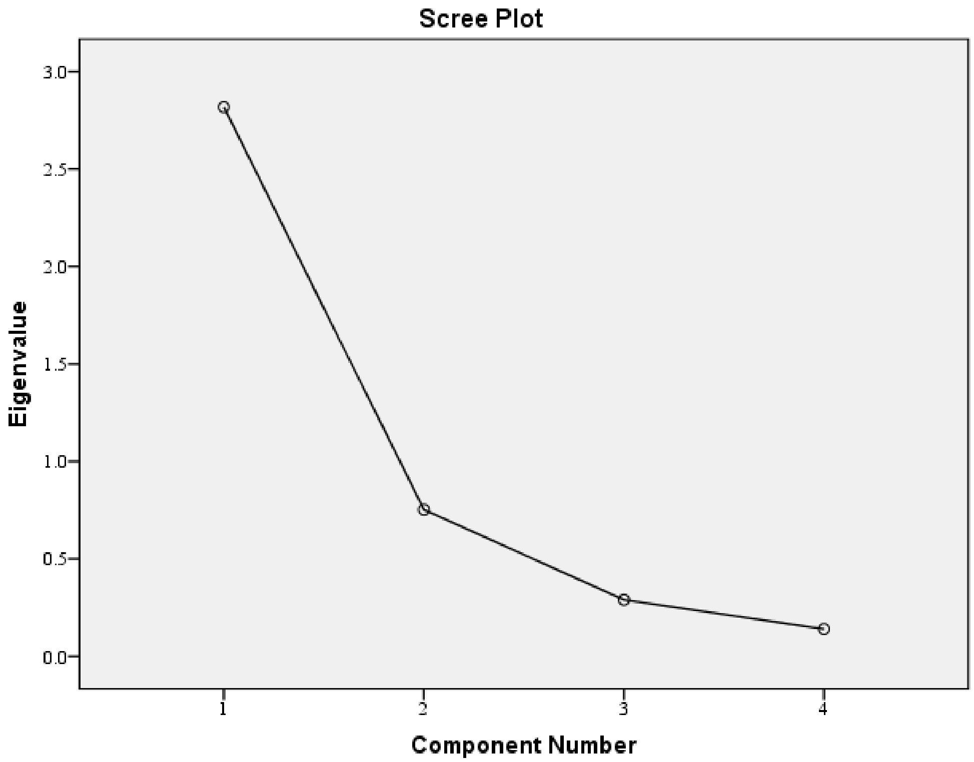
	Initial	Extraction
Openness to Storing Public Runoffs	1.000	.656
Openness to Infiltrating Public Runoffs	1.000	.653
Openness to Water Transportation	1.000	.781
Openness to Canals and Creeks	1.000	.728

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.818	70.440	70.440	2.818	70.440	70.440
2	.752	18.810	89.250			
3	.290	7.252	96.502			
4	.140	3.498	100.000			

Extraction Method: Principal Component Analysis.



Component Matrix[a]

	Component
	1
Openness to Storing Public Runoffs	.810
Openness to Infiltrating Public Runoffs	.808
Openness to Water Transportation	.884
Openness to Canals and Creeks	.853

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Reproduced Correlations

		Openness to Storing Public Runoffs	Openness to Infiltrating Public Runoffs	Openness to Water Transportation	Openness to Canals and Creeks
Reproduced Correlation	Openness to Storing Public Runoffs	.656[a]	.654	.716	.691
	Openness to Infiltrating Public Runoffs	.654	.653[a]	.714	.689
	Openness to Water Transportation	.716	.714	.781[a]	.754
	Openness to Canals and Creeks	.691	.689	.754	.728[a]
Residual[b]	Openness to Storing Public Runoffs		.056	-.176	-.197
	Openness to Infiltrating Public Runoffs	.056		-.172	-.203
	Openness to Water Transportation	-.176	-.172		.103
	Openness to Canals and Creeks	-.197	-.203	.103	

Extraction Method: Principal Component Analysis.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 6 (100.0%) nonredundant residuals with absolute values greater than 0.05.

Component Score Coefficient Matrix

	Component
	1
Openness to Storing Public Runoffs	.287
Openness to Infiltrating Public Runoffs	.287
Openness to Water Transportation	.314
Openness to Canals and Creeks	.303

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
Component Scores.

Component Score Covariance Matrix

Component	1
1	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
Component Scores.

APPENDIX O

RESULTS OF MACRO-LEVEL MEDIATION ANALYSES

Run MATRIX procedure:

****

Preacher and Hayes (2008) SPSS Macro for Multiple Mediation

Written by Andrew F. Hayes, The Ohio State University

http://www.comm.ohio-state.edu/ahayes/

For details, see Preacher, K. J., & Hayes, A. F. (2008). Asymptotic

and resampling strategies for assessing and comparing indirect effects

in multiple mediator models. Behavior Research Methods, 40, 879-891.

****
------ END MATRIX -----

Model A
Dependent, Independent, and Proposed Mediator Variables:
DV = C0_C (allocentric aquaphilia)
IV = WQ (high or low water city)
MEDS = PCS_AU (aquaphilic urbanism)

Sample size
60

IV to Mediators (a paths)

	Coeff	se	t	p
PCS_AU	1.4604	.3512	4.1586	.0001

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
PCS_AU	.3384	.0759	4.4568	.0000

Total Effect of IV on DV (c path)

	Coeff	se	t	p
WQ	.6441	.2338	2.7553	.0078

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
WQ	.1499	.2314	.6479	.5196

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.3443	.3212	14.9621	2.0000	57.0000	.0000

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.4942	.4979	.0037	.1791
PCS_AU	.4942	.4979	.0037	.1791

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.1913	.8970
PCS_AU	.1913	.8970

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

********************************* NOTES********************************
------ END MATRIX -----

Model B
Dependent, Independent, and Proposed Mediator Variables:
DV = FAC1_2 (openness toward water-coherent urbanism)
IV = WQ (high or low water city)
MEDS = PCS_AU (aquaphilic urbanism)

Sample size
60

IV to Mediators (a paths)

	Coeff	se	t	p
PCS_AU	1.4604	.3512	4.1586	.0001

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
PCS_AU	.1788	.0849	2.1057	.0396

Total Effect of IV on DV (c path)

	Coeff	se	t	p
WQ	.3127	.2337	1.3378	.1862

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
WQ	.0516	.2588	.1992	.8428

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.0999	.0684	3.1648	2.0000	57.0000	.0497

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.2611	.2717	.0106	.1487
PCS_AU	.2611	.2717	.0106	.1487

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0314	.6102
PCS_AU	.0314	.6102

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

********************************* NOTES********************************
------ END MATRIX -----

Model C
Dependent, Independent, and Proposed Mediator Variables:
DV = FAC1_2 (openness toward water-coherent urbanism)
IV = PCS_AU (aquaphilic urbanism)
MEDS = C0_C (allocentric aquaphilia)

Sample size
60

IV to Mediators (a paths)

	Coeff	se	t	p
C0_C	.3620	.0663	5.4592	.0000

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
C0_C	.3083	.1419	2.1730	.0339

Total Effect of IV on DV (c path)

	Coeff	se	t	p
PCS_AU	.1869	.0739	2.5290	.0142

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
PCS_AU	.0753	.0882	.8544	.3965

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.1682	.1390	5.7641	2.0000	57.0000	.0052

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.1116	.1070	-.0046	.0438
C0_C	.1116	.1070	-.0046	.0438

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0413	.2225
C0_C	.0413	.2225

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model C_1
Dependent, Independent, and Proposed Mediator Variables:
DV = FAC1_2 (openness toward water-coherent urbanism)
IV = FAC1_1 (water-based goal affordance)
MEDS = C0_C (allocentric aquaphilia)

Sample size
60

IV to Mediators (a paths)

	Coeff	se	t	p
C0_C	.4716	.1090	4.3271	.0001

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
C0_C	.3766	.1335	2.8215	.0066

Total Effect of IV on DV (c path)

	Coeff	se	t	p
FAC1_1	.1821	.1172	1.5534	.1258

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
FAC1_1	.0045	.1274	.0355	.9718

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.1576	.1280	5.3316	2.0000	57.0000	.0075

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.1776	.1746	-.0030	.0593
C0_C	.1776	.1746	-.0030	.0593

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0878	.3381
C0_C	.0878	.3381

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model C_2
Dependent, Independent, and Proposed Mediator Variables:
DV = FAC1_2 (openness toward water-coherent urbanism)
IV = FAC2_1 (water-based imageability)
MEDS = C0_C (allocentric aquaphilia)

Sample size
60

IV to Mediators (a paths)

	Coeff	se	t	p
C0_C	.4511	.1105	4.0839	.0001

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
C0_C	.2777	.1286	2.1594	.0350

Total Effect of IV on DV (c path)

	Coeff	se	t	p
FAC2_1	.3298	.1116	2.9568	.0045

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
FAC2_1	.2046	.1228	1.6663	.1011

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.1967	.1685	6.9788	2.0000	57.0000	.0019

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)
Data Boot Bias SE

TOTAL	.1253	.1194	-.0059	.0541
C0_C	.1253	.1194	-.0059	.0541

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0417	.2859
C0_C	.0417	.2859

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

********************************* NOTES*********************************

APPENDIX P

RESULTS OF MICRO-LEVEL MEDIATION ANALYSES

Run MATRIX procedure:

****

Preacher and Hayes (2008) SPSS Macro for Multiple Mediation

Written by Andrew F. Hayes, The Ohio State University

http://www.comm.ohio-state.edu/ahayes/

For details, see Preacher, K. J., & Hayes, A. F. (2008). Asymptotic

and resampling strategies for assessing and comparing indirect effects

in multiple mediator models. Behavior Research Methods, 40, 879-891.

****

------ END MATRIX -----

Model D

Dependent, Independent, and Proposed Mediator Variables:
DV = Co_2B (dua-perspective coherence)
IV = H2 (gender)
MEDS = A1_C (canal mappability)
B1_C (canal identifiability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	-1.5726	.8602	-1.8281	.0738
B1_C	-1.3638	.6357	-2.1454	.0370

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.3480	.1188	2.9305	.0053
B1_C	-.2557	.1607	-1.5913	.1184

Total Effect of IV on DV (c path)

	Coeff	se	t	p
H2	-.4240	.6383	-.6643	.5097

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
H2	-.2255	.6305	-.3576	.7223

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.9604	.3800	-2.5275	.0150

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.2634	.1994	4.1128	4.0000	46.0000	.0062

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	-.1985	-.2036	-.0051	.3236
A1_C	-.5473	-.5619	-.0145	.3527
B1_C	.3488	.3583	.0095	.2673

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	-.9262	.3735
A1_C	-1.4828	-.0305
B1_C	-.0106	1.0886

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

*********************************** NOTES***********************************
------ END MATRIX -----

Model E
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ca (dual-perspective coherence)

IV = H2 (gender)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)

Sample size
56

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	-1.7472	.7955	-2.1965	.0325

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.2114	.0406	5.2110	.0000

Total Effect of IV on DV (c path)

	Coeff	se	t	p
H2	-.6202	.2871	-2.1599	.0353

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
H2	-.2508	.2454	-1.0218	.3116

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.5530	.1469	-3.7649	.0004

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.4948	.4656	16.9757	3.0000	52.0000	.0000

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	-.3694	-.3751	-.0056	.1752
A1_C	-.3694	-.3751	-.0056	.1752

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	-.7524	-.0652
A1_C	-.7524	-.0652

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model F
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ce (water-based egocentric coherence)
IV = H2 (gender)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	-1.5726	.8602	-1.8281	.0738

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.1184	.0345	3.4325	.0013

Total Effect of IV on DV (c path)

	Coeff	se	t	p
H2	-.3644	.2274	-1.6025	.1156

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
H2	-.1783	.2125	-.8390	.4057

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.2867	.1301	-2.2036	.0325

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p

.3076 .2634 6.9596 3.0000 47.0000 .0006

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	-.1861	-.1894	-.0033	.1055
A1_C	-.1861	-.1894	-.0033	.1055

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	-.4428	-.0226
A1_C	-.4428	-.0226

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model G
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_2B (dual-perspective coherence)
IV = TR (visitors or residents)
MEDS = A1_C (canal mappability)
B1_C (canal identifiability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	1.3545	.7756	1.7464	.0871
B1_C	-.3926	.5956	-.6591	.5130

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.3016	.1252	2.4085	.0201
B1_C	-.1913	.1631	-1.1730	.2468

Total Effect of IV on DV (c path)

	Coeff	se	t	p
TR	1.1271	.5531	2.0379	.0471

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
TR	.6436	.5734	1.1224	.2675

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.9562	.3608	-2.6504	.0110

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.2811	.2185	4.4959	4.0000	46.0000	.0038

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.4835	.5202	.0366	.3182
A1_C	.4085	.4366	.0281	.3135
B1_C	.0751	.0836	.0085	.1562

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	-.0159	1.2576
A1_C	-.0214	1.2210
B1_C	-.1206	.5745

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model H

Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ca (water-based allocentric coherence)
IV = TR (visitors or residents)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)

Sample size
56

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	1.3247	.7272	1.8217	.0741

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.2358	.0398	5.9235	.0000

Total Effect of IV on DV (c path)

	Coeff	se	t	p
TR	.0329	.2702	.1219	.9035

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
TR	-.2795	.2173	-1.2864	.2040

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.5998	.1404	-4.2708	.0001

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.5005	.4717	17.3707	3.0000	52.0000	.0000

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.3124	.3130	.0006	.1899
A1_C	.3124	.3130	.0006	.1899

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	-.0115	.7501
A1_C	-.0115	.7501

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model J_1
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_2B (dual-perspective coherence)
IV = B1_C (canal identifiability)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	.7223	.1669	4.3268	.0001

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.3480	.1188	2.9305	.0053

Total Effect of IV on DV (c path)

	Coeff	se	t	p
B1_C	-.0044	.1465	-.0299	.9763

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
B1_C	-.2557	.1607	-1.5913	.1184

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.9604	.3800	-2.5275	.0150
H2	-.2255	.6305	-.3576	.7223

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.2634	.1994	4.1128	4.0000	46.0000	.0062

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.2514	.2566	.0052	.1096
A1_C	.2514	.2566	.0052	.1096

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0848	.5126
A1_C	.0848	.5126

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model J_2
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_2B (dual-perspective coherence)
IV = B1_C (canal identifiability)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
TR (visitors or residents)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	.7981	.1501	5.3168	.0000

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.3016	.1252	2.4085	.0201

Total Effect of IV on DV (c path)

	Coeff	se	t	p
B1_C	.0494	.1353	.3653	.7165

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
B1_C	-.1913	.1631	-1.1730	.2468

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.9562	.3608	-2.6504	.0110
TR	.6436	.5734	1.1224	.2675

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.2811	.2185	4.4959	4.0000	46.0000	.0038

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.2407	.2551	.0145	.1243
A1_C	.2407	.2551	.0145	.1243

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0634	.5555
A1_C	.0634	.5555

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model K_1
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ca (water-based allocentric coherence)
IV = B1_C (canal identifiability)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)

Sample size
56

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	.6605	.1618	4.0830	.0002

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.1839	.0464	3.9607	.0002

Total Effect of IV on DV (c path)

	Coeff	se	t	p
B1_C	.1964	.0613	3.2026	.0023

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
B1_C	.0750	.0622	1.2045	.2340

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.5508	.1463	-3.7659	.0004
H2	-.2180	.2459	-.8864	.3796

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.5088	.4702	13.2048	4.0000	51.0000	.0000

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.1214	.1234	.0020	.0462
A1_C	.1214	.1234	.0020	.0462

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0507	.2295
A1_C	.0507	.2295

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

****************************** NOTES******************************
------ END MATRIX -----

Model K_2
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ca (water-based allocentric coherence)
IV = B1_C (canal identifiability)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
TR (visitors or residents)

Sample size
56

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	.7850	.1494	5.2528	.0000

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.2088	.0493	4.2342	.0001

Total Effect of IV on DV (c path)

	Coeff	se	t	p
B1_C	.2251	.0612	3.6781	.0006

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
B1_C	.0611	.0658	.9298	.3569

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.5922	.1409	-4.2041	.0001
TR	-.2064	.2313	-.8924	.3764

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.5089	.4703	13.2102	4.0000	51.0000	.0000

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.1639	.1661	.0021	.0578
A1_C	.1639	.1661	.0021	.0578

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0693	.3044
A1_C	.0693	.3044

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model L_1
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ce (water-based egocentric coherence)
IV = B1_C (canal identifiability)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)

H2 (gender)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	.7223	.1669	4.3268	.0001

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.1161	.0412	2.8174	.0071

Total Effect of IV on DV (c path)

	Coeff	se	t	p
B1_C	.0896	.0505	1.7728	.0827

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
B1_C	.0057	.0558	.1024	.9189

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.2877	.1319	-2.1818	.0343
H2	-.1741	.2188	-.7956	.4303

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.3077	.2476	5.1124	4.0000	46.0000	.0017

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.0839	.0873	.0034	.0346
A1_C	.0839	.0873	.0034	.0346

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0351	.1810
A1_C	.0351	.1810

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

********************************** NOTES**********************************
------ END MATRIX -----

Model L_2
Dependent, Independent, and Proposed Mediator Variables:
DV = Co_Ce (water-based egocentric coherence)
IV = B1_C (canal identifiability)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
TR (visitors or residents)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	.7981	.1501	5.3168	.0000

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.1529	.0422	3.6245	.0007

Total Effect of IV on DV (c path)

	Coeff	se	t	p
B1_C	.1014	.0487	2.0822	.0428

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
B1_C	-.0206	.0549	-.3756	.7089

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.3476	.1216	-2.8589	.0064
TR	-.4174	.1932	-2.1600	.0360

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.3628	.3074	6.5489	4.0000	46.0000	.0003

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.1220	.1267	.0047	.0444
A1_C	.1220	.1267	.0047	.0444

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0589	.2329
A1_C	.0589	.2329

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES*******************************
------ END MATRIX -----

Model M

Dependent, Independent, and Proposed Mediator Variables:
DV = C1_C (canal attachment)
IV = Co_Ca (water-based allocentric coherence)
MEDS = B1_C (canal identifiability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)
TR (visitors or residents)

Sample size
56

IV to Mediators (a paths)

	Coeff	se	t	p
B1_C	.8281	.2591	3.1964	.0024

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p

B1_C	.6098	.1387	4.3962	.0001

Total Effect of IV on DV (c path)

	Coeff	se	t	p
Co_Ca	.6172	.2992	2.0629	.0442

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
Co_Ca	.1123	.2811	.3993	.6913

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.1110	.3623	-.3065	.7605
H2	-.2874	.5741	-.5007	.6188
TR	-.0380	.5000	-.0759	.9398

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.3786	.3164	6.0919	5.0000	50.0000	.0002

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.5049	.5022	-.0027	.1730
B1_C	.5049	.5022	-.0027	.1730

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.2326	.9351
B1_C	.2326	.9351

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model M_1

DV = C1_C (canal attachment)
IV = Co_Ca (water-based allocentric coherence)
MEDS = A1_C (canal mapability)
B1_C (canal identifiability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)
TR (visitors or residents)

Sample size
56

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	1.6402	.3020	5.4310	.0000
B1_C	.8281	.2591	3.1964	.0024

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.0929	.1322	.7027	.4856
B1_C	.5636	.1541	3.6564	.0006

Total Effect of IV on DV (c path)

	Coeff	se	t	p
Co_Ca	.6172	.2992	2.0629	.0442

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
Co_Ca	-.0019	.3259	-.0057	.9955

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	-.1922	.3820	-.5030	.6172
H2	-.2702	.5775	-.4679	.6419
TR	-.1831	.5434	-.3370	.7376

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.3848	.3094	5.1074	6.0000	49.0000	.0004

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.6190	.6253	.0063	.2000
A1_C	.1524	.1672	.0149	.2190
B1_C	.4667	.4580	-.0086	.1880

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.2489	1.0663
A1_C	-.1904	.6858
B1_C	.1605	1.0056

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model O
Dependent, Independent, and Proposed Mediator Variables:
DV = C1_C (canal attachment)
IV = Co_Ce (water-based egocentric coherence)
MEDS = A1_C (canal mappability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)
TR (visitors or residents)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	1.8909	.4754	3.9772	.0002

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.2822	.1222	2.3095	.0256

Total Effect of IV on DV (c path)

	Coeff	se	t	p

Co_Ce   1.0404   .4122   2.5241   .0151

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
Co_Ce	.5068	.4568	1.1094	.2731

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	.0581	.4144	.1401	.8892
H2	-.8589	.6402	-1.3416	.1865
TR	-.3760	.5974	-.6294	.5323

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.2879	.2087	3.6381	5.0000	45.0000	.0075

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.5336	.5495	.0158	.3312
A1_C	.5336	.5495	.0158	.3312

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	.0858	1.4636
A1_C	.0858	1.4636

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model O_1
Dependent, Independent, and Proposed Mediator Variables:
DV =   C1_C (canal attachment)
IV =   Co_Ce (water-based egocentric coherence)
MEDS = B1_C (canal identifiability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)
TR (visitors or residents)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
B1_C	.6558	.4029	1.6276	.1104

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
B1_C	.5362	.1299	4.1289	.0002

Total Effect of IV on DV (c path)

	Coeff	se	t	p
Co_Ce	1.0404	.4122	2.5241	.0151

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
Co_Ce	.6888	.3650	1.8872	.0656

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	.0654	.3645	.1795	.8583
H2	-.4254	.5915	-.7193	.4757
TR	.2952	.5079	.5811	.5641

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.4223	.3581	6.5793	5.0000	45.0000	.0001

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.3516	.3774	.0257	.2609
B1_C	.3516	.3774	.0257	.2609

Bias Corrected Confidence Intervals

Lower	Upper

TOTAL	-.0642	1.0020
B1_C	-.0642	1.0020

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************
------ END MATRIX -----

Model O_2
Dependent, Independent, and Proposed Mediator Variables:
DV = C1_C (canal attachment)
IV = Co_Ce (water-based egocentric coherence)
MEDS = A1_C (canal mappability)
B1_C (canal identifiability)

Statistical Controls:
CONTROL= D1_R (aquaphilia sensitivity baseline)
H2 (gender)
TR (visitors or residents)

Sample size
51

IV to Mediators (a paths)

	Coeff	se	t	p
A1_C	1.8909	.4754	3.9772	.0002
B1_C	.6558	.4029	1.6276	.1104

Direct Effects of Mediators on DV (b paths)

	Coeff	se	t	p
A1_C	.0431	.1337	.3227	.7484
B1_C	.5079	.1577	3.2200	.0024

Total Effect of IV on DV (c path)

	Coeff	se	t	p
Co_Ce	1.0404	.4122	2.5241	.0151

Direct Effect of IV on DV (c' path)

	Coeff	se	t	p
Co_Ce	.6257	.4172	1.4998	.1408

Partial Effect of Control Variables on DV

	Coeff	se	t	p
D1_R	.0391	.3771	.1036	.9180
H2	-.4289	.5975	-.7178	.4767
TR	.2125	.5734	.3707	.7127

Model Summary for DV Model

R-sq	Adj R-sq	F	df1	df2	p
.4237	.3451	5.3910	6.0000	44.0000	.0003

****

BOOTSTRAP RESULTS FOR INDIRECT EFFECTS

Indirect Effects of IV on DV through Proposed Mediators (ab paths)

	Data	Boot	Bias	SE
TOTAL	.4147	.4433	.0286	.3699
A1_C	.0816	.1053	.0238	.2912
B1_C	.3331	.3380	.0049	.2672

Bias Corrected Confidence Intervals

	Lower	Upper
TOTAL	-.1381	1.3499
A1_C	-.4680	.7368
B1_C	-.0158	1.1258

****

Level of Confidence for Confidence Intervals:
95

Number of Bootstrap Resamples:
1000

******************************** NOTES********************************

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