Capturing the stories of our lives:

Examining the collection of life narrative data

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Abstract

Objective: Do different methods for collecting life narratives – the integrated, autobiographical construction of the past and imagined future – produce similar lexical features and relationships to personality traits? The present study compares accounts from an in-person and online sample on measures of word categories, narrative themes and their relationships with Big Five traits.

Method: The first sample ($N = 157$, $M_{age} = 53.7$, 64% female, 55% White, and 43% Black) consisted of narratives gathered in-person and the second ($N = 256$, $M_{age} = 30.6$, 61% female, 70% White, 30% non-White) contained type-written responses to the same prompts from an independent online sample. Participants' responses to the narrative prompts were coded for thematic redemption and contamination.

Results: Tests revealed significant differences between samples in 25 of 63 LIWC word categories. Online participants' narratives also had higher odds of thematic redemption (but not contamination) above and beyond word count, type of narrative scene, participant demographics, and Big Five traits. Lastly, comparisons revealed no significant differences across the samples' relationships between personality traits and narrative themes.

Conclusion: This research supports conditional assimilation of correlational findings from different narrative methodologies and proposes methodological considerations for future research involving life narratives.

Keywords: *life story, online samples, narrative, methodology, Big Five*

Capturing the stories of our lives:

Examining the methodology of narrative data collection

The purpose of this investigation is to compare two different approaches for the collection of autobiographical narrative data – in-person interviews versus online prompts. Historically, narrative accounts of life events have been collected in a lab via face-to-face meetings with trained interviewers. As new technological advancements are incorporated to collect data, however, a growing number of psychological researchers have explored telemetric (i.e., online or web-based) collection methods. Do these two different methods generate comparable results?

Life narratives

While self-report personality inventories have been most commonly utilized in the field of personality psychology, researchers are increasingly relying on narrative methodology – analyzing an individual's personality characteristics through their *life narrative*. Through the integration of events from the reconstructed past and the imagined future, a life narrative typically includes settings, characters, plots, and themes (McAdams & Guo, 2015). To study a person's life narrative, researchers have asked participants to disclose specific moments in their life, such as a major high or low point, which serve as landmark events in their understanding of themselves. These narrative accounts are then quantitatively coded by trained researchers for variables such as lexical word categories and thematic ideas. For example, narratives have been coded for linguistic word choice and structure (Franzosi, 1998; Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010), changes in emotional valence (Cox & McAdams, 2014), and affective themes such as *redemption* (narrating positive meaning or outcomes following negative events) and *contamination sequences* (narrating initially positive events resulting in subsequent negative outcomes) (McAdams, Reynolds, Lewis, Patten, & Bowman, 2001). Though analyses of themes have traditionally been conducted on autobiographical narrative accounts collected in-person by a trained interviewer, a variety of other collection methods (i.e., written or typed in the absence of an interviewer) are increasingly used by researchers interested in examining narratives. Consequently, relevant to narrative research is understanding whether different approaches towards collecting narratives yield accounts of similar lexical and thematic structure.

Psychologists have employed life narratives to study a range of associations between narrative themes and personality characteristics. For instance, highly generative people (i.e., individuals with strong commitments or concerns for the well-being of others) tend to tell life stories rich with redemption sequences (McAdams, Diamond, de St. Aubin, & Mansfield, 1997; McAdams et al., 2001). Later studies have demonstrated that highly generative people tend to narrate those redemption sequences within a suite of themes, which when taken together, comprise of a prototypical life narrative termed the *redemptive self* (McAdams, 2006b, 2006/2013). This redemptive self composite was most common among those who scored higher on levels of public service motivation and psychosocial well-being (McAdams, 2013b; McAdams & Guo, 2015). Recently, the redemptive self composite was found to be associated with Big Five personality traits representing socioemotional maturity – high agreeableness, conscientiousness, extraversion, and emotional stability (Guo, Klevan, & McAdams, 2016).

The utilization of narrative methods extends beyond the domain of Big Five personality. Personality researchers have found that the ways in which individuals make sense of their lives have consequences for psychosocial well-being (Adler, Lodi-Smith, Phillippe, & Houle, 2016; Adler et al., 2017; McAdams & Guo, 2015; McAdams& McLean, 2013) and health. For example, a study has shown that alcoholics with more coded redemption sequences in autobiographical accounts of their last drink also enjoyed longer subsequent periods of sobriety (Dunlop & Tracy, 2013). Narrative themes of agency (demonstrated by accounts of self-mastery, achievement, and empowerment) have also been found to be predictive of improvements among psychotherapy patients (Adler, 2012). Outside of psychology, researchers have used narrative inquiry in other fields as a medium to understand how: individuals interpret culture and life events (Radin, 1926; Wolcott, 1999), meaning making influences a body's immune function (Bower, Kemeny, Taylor, & Fahey, 1998) and rate of healing from illness (Charon, 2001; Mattingly & Garro, 2000), and how narrative construction affects academic outcomes for both teachers (Cortazzi, 2014) and first-generation students (Stephens, Hamedani, & Destin, 2014). As researchers continue to study the broad components of narratives under a multimethod framework, the question arises: Do different methods of narrative collection produce comparable empirical results?

Methods of narrative collection: In-person interviewing v. online prompts

There are two predominant and distinctive methodologies (i.e., in-person and online prompting) that researchers have used to capture the stories of participants' lives. The first traditionally relies on in-person interviewing conducted by a trained interviewer with a structured script, to provide details of their significant life events. Their verbal responses to the questions are audio recorded and may even be transcribed into a document with linguistic emphases and pauses. Recent improvements in computational data-gathering have resulted in an increase in usage of a second technique to collect narrative data – the telemetric method, specifically via online text prompts. A review of major journal articles using narrative research published between 2008-2014 found that approximately 11% of studies had used online collection methods, instructing research subjects to type out their responses to prompts online. Research websites may provide free feedback in return for participation completion (see the SAPA Project: https://sapa-project.org; Condon & Revelle, 2015; Weston, Cox, Condon, & Jackson, 2015). Other websites through companies like Qualtrics and Amazon Mechanical Turk (MTurk) offer researchers a platform for recruiting qualifying participants to be surveyed for studies in exchange for payment. Compared to in-person interviewing, telemetric methods of collecting narratives require far less human interaction, if any at all.

The two methods described – in-person interviewing and online narrative collections – are on opposite ends of the spectrum in terms of human interaction with the participant. Currently, researchers utilize a broad set of methodologies within that range (i.e., phone interviews with a trained interviewer, or in-lab narrative written prompt). Once provided by the participant, narrative accounts can then be transcribed into easier-to-process Word documents, or directly analyzed for narrative themes and linguistic properties. During the analysis of thematic content, reasonable interrater reliability must be achieved by at least two coders (Adler et al., 2017; Murray, 2015).

There are key advantages and disadvantages, then, to both collection methodologies at the two ends of this continuum. The first is a surface-level, albeit important, distinction between the amount of resources required beyond participant recruitment for in-person versus telemetric collection. For traditional in-person interviews, having the presence of a trained interviewer and a participant within a research space comes with potential costs in terms of both time (i.e., commute time for the participant, training of interviewers) and money (i.e., lab space, payment for commuting and the interviewer, transcription service for the recorded narrations). In comparison, online prompts are generally cheaper to maintain. Once the initial costs of setting up the platform and maintenance of the site are expended, participants may complete prompts anywhere there is an internet connection, eliminating the need for a lab visit or for voice-to-text transcription. As a result, researchers using online methods can easily collect data from more participants than may be managed in an in-person setting.

The presence or absence of an interviewer is a second differentiating factor between in-person and online narrative collection. The narratives obtained using conventional in-person interview methods have been shown to be data-rich – full of qualitative insights into participants' personality, identity, development, psychological well-being, and social relationships (McAdams, 2001). This may be due to the role of a trained interviewer to be an active listener, keeping the participant on task during the interview by reminding participants to fully answer the scripted prompt. The resulting narrative response is often a longer and more specified response than would be expected from those narrative accounts collected online, though there may be additional variation due to different interviewer effects (i.e., some interviewers may be more encouraging of eliciting details from participants or provide an environment where participants are more likely to display emotion through tone or body language). However, these differences due to interviewer effects can be reduced through utilization of standardized, structured narrative interviews and training. On the other hand, the absence of an interviewer with online narrative collection, while standardizing the experience for participants, can raise the problem of compliance. Participants without a guiding interviewer may not be as mindful of providing a narrative that answers the complete prompt, resulting in impoverished, less-detailed narrative data.

As interest in life narratives has grown, scientists are increasingly incorporating narrative studies and integrating results from various narrative collection methodologies to inform their research; in doing so, running into questions of generalizability and validity. Empirical evaluations of survey data collected in-person and online suggest that Internet self-report questionnaires, test, and assessments are consistent with those data collected in the lab (Gosling, Vazire, Srivastava, & John, 2004; Wilt, Condon, & Revelle, 2011). However, findings are more mixed regarding life narrative methods. Initial research by Grysman (2015) indicates an effect of online anonymity, such that narratives typed online via MTurk tend to be shorter but more emotionally-valenced than those provided with an experimenter present. Other findings point instead to the effects of response format – the reflective act of writing lends itself to more linguistically rich narratives versus verbal accounts of life narratives (McCoy & Dunlop, 2017). Thus, this current research will add to the nascent literature examining whether the method (i.e., in-person versus online) of collecting life narratives may result in differences within the lexical and thematic content of narratives. Moreover, this research will be the first work to examine whether narrative collection methodology has an influence upon the nature of the relationships between narrative themes and Big Five personality traits.

Two ways to code narratives: Lexical and thematic analyses

Researchers interested in life narratives have generally examined responses in two ways – linguistically and thematically. Linguistic analysis programs like Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, & Francis, 2001), have provided an opportunity for researchers to examine the complexity of lexical structure within texts. Frequency analyses of specific words categories (i.e., personal pronouns or affect-related words) allow researchers to computationally assess the structural components and verbal patterns of words within transcribed documents (Weston et al., 2015). Utilization of automated linguistic analyses on written narratives have indicated that specific word patterns are associated with Big Five personality traits (Hirsch & Peterson, 2009) and adaptation to major health events (Robbins, Mehl, Smith, & Weihs, 2013).

The second approach researchers have taken towards analyzing life narratives focuses on the affective and motivational thematic content of participant responses. Studies have indicated that there are individual variations in the salience of redemption and contamination sequences in autobiographical narratives and those variations are related to important psychological outcomes (McAdams et al., 1997; McAdams et al., 2001). For instance, life narratives rich in themes of redemption sequences have been associated with psychological well-being, emotional adjustment, generativity, and positive socioemotional personality traits (Adler et al., 2015; Dumas, Lawford, Tieu, & Pratt, 2009; Guo et al., 2016; McAdams et al., 2001; McAdams & Guo, 2015). Past research has also demonstrated a connection between contamination sequences and depression (Adler, Kissel, & McAdams, 2006; McAdams & Guo, 2015).

Despite the increasing use of life narrative scenes collected on the Internet over the last decade, very little is known about whether the relationships between the content of narratives and variables of interests are comparatively different from samples collected verbally in-person by a trained interviewer and those typed in response to online prompts. Using a common structured script to obtain participants' high and low points from two collection methodologies (i.e., verbally in-person and typed online), this current project will: 1) assess whether affect-related, functional, and pronoun word differences exist in linguistic usage between participants; 2) explore whether rates of two motivational themes – redemption and contamination sequences – differ between participants; and 3) test whether relationships between Big Five and affective narrative themes of redemption and contamination will vary depending on method of narrative account collection.

Method

In-person sample

In-person interview participants. For the in-person sample, community adults from the Greater Chicago area (N= 163; 64% female) ranging from ages 51 to 56 years (*M* = 53.71, *SD* = 1.07) were recruited in 2008 as part of a longitudinal study of adult personality development (see: Cox & McAdams, 2014; Guo et al., 2016; Manczak, Zapata-Gietl, & McAdams, 2014; McAdams & Guo, 2015). In this sample, 55% of participants described themselves as White, 43% Black, and 2% as interracial or "other." Annual household incomes ranged between under $25,000 to over $300,000, with a median income of $75,000-100,000. A large majority of the participants were college educated: 6% received a high school diploma only, 27% attended some college, 24% graduated college, and 44% completed a graduate education.

In-person life narrative interviews. Prior to interviewing, each participant completed a 2-hour online survey that included self-reported demographics, personality. and psychological well-being measures. Participants were then administered by a trained interviewer the standardized life narrative interview adapted from previous studies of narratives (McAdams et al., 1997). The current study examined responses for 2 discrete scenes of the full interview – 1) a high point (the greatest or happiest moment in the story of your life) and (2) a low point (the worst or unhappiest moment in the story). For each narrative response, the participants were asked to describe what happened in the scene, what they were thinking and feeling at the time, and what they thought the scene said about themselves or about their life story. While scenes such as autobiographical high and low points do not capture the complete scope of what constitutes a person's overall life narrative, responses to these key scene prompts have proven to be exceptionally revealing of the main themes that characterize narrative identity – a person's internalized and evolving story of the self that provides a sense of unity and purpose in living (McAdams, 1985; McAdams & McLean, 2013; McAdams & Manczak, 2015). The high and low point prompts are provided under *Appendix A*.

Responses to the two scenes were audio-recorded and transcribed, with a combined range of 69 to 2,990 words (M = 698, SD = 473). Then, the accounts were separately analyzed for the presence (+1) or absence (0) of redemption and contamination sequences by two independent coders who were blind to participant identifiers. Theme scores were separately averaged across high and low point scenes to arrive at a total score (ranging from 0 to 2) illustrating the salience of the specific theme for the participant. For each thematic category, coders' scores were pooled and averaged for subsequent data analysis. The two themes for analyses were well-validated constructs and defined as follows (Adler et al., 2006; McAdams et al., 1997):

Redemption Sequence: The narrator describes a movement from a demonstrably negative situation to a positive outcome. The redemptive move may either (1) be described in real-time sequence as the original event or (2) represent a positive interpretation of the original negative scene that the narrator formulated after the scene occurred. Coding reliability: ICC2k = .87; κ = .75.

Contamination Sequence: The narrator describes a movement from a discernible initially positive event to a subsequently negative outcome. Previous life-narrative studies have found contamination sequences to be associated with low life satisfaction (Adler et al., 2006; McAdams & Guo, 2015). Coding reliability: ICC2k = .44; κ = .27.

In-person Big Five traits. The broad traits of agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience were measured using the NEO Five Factor Inventory (NEO-FFI; McCrae & Costa, 2004). Each trait was separately measured using a sub-scale of 12 self-report items, with responses ranging from "1 = *strongly disagree*" to "5 = *strongly agree*." The NEO-FFI is a highly reliable and valid, revised, 60-item version of the original 240-item NEO Personality Inventory (NEO-PI; Costa & McCrae, 1985). In the current study, all five sub-scales had acceptable internal consistency (alphas ranged from .72 to .86).

Online sample

Online sample participants. The online sample contained narrative accounts from 256 individuals (61% female) collected between October 2013 – August 2014 from SAPA-project.org in exchange for customized feedback about their personality. Participants in the online sample ranged between 14 – 82 years of age (M = 30.61, SD = 13.90) and represented 13 countries (93% were from the U.S.). The racial makeup was self-reported as 70% White, 9% Hispanic/Latino, 8% multi-racial, 7% Asian, and 4% Black. The educational levels in the online sample had considerable range: 12% had fewer than 12 years of education, 19% were high school graduates, 34% were currently in college, 23% had obtained a college degree, and 12% had a graduate degree.

Online life narrative prompts. Participant first filled out a 20-minute online survey which included demographic and personality questions. Then, those who voluntarily chose to write narratives were randomly assigned to either a high or a low point prompt, like the ones used in the in-person interviews (see *Appendix A*). Of the 67,190 total participants, 396 volunteered to write a narrative, of which 64.6% (N = 256) contained at least 50 words (M = 248, SD = 196, max = 1,329). The pre-hoc 50-word exclusion criteria ensured that responses were qualitatively sufficient for lexical and thematic coding (demographic differences between those who volunteered to provide narratives and those who did not are reported in the Results). Two independent coders (one was a coder for the in-person interview sample), blind to the identifying information of participants, determined the presence (+1) or absence (0) of redemption (ICC2k = .88; κ = .78) and contamination (ICC2k = .65; κ = .48).

Online Big Five traits. To assess Big Five traits, the 100-item International Personality Item Pool (IPIP; Goldberg, 1999), a highly valid and reliable measure was used. Internal consistency values were high (alphas ranged from .90 to .94).

Analysis procedures

Data were first standardized within samples to ensure that variables were on common scales. To assess differences in thematic content, hierarchical linear models where narratives were nested within participant were employed. This type of modelling allowed for the simultaneous inclusion of both the high and low point of each in-person interview participant, while accounting for the dependence between these narratives. Level 1 refers to the narrative level and level 2 refers to the person level (for the online participants, levels 1 and 2 are synonymous since there was only one narrative per participant). Big Five traits were incorporated as control variables within these hierarchical regression models predicting rates of redemption and contamination sequences, as there was concern that Big Five traits may influence the relationship between collection methodology and rates of coded narrative themes (e.g., those low in extraversion may feel more comfortable divulging stories that may be more redemptive or contaminated when they are in an interview, but the same tendency may not occur online). All analyses were conducted using R (R Core Team, 2016).

Results

The two samples had broad variation in educational attainment, race, and gender, and differed substantially in their demographic makeup. Though there were no significant differences in the gender ratio, the in-person interview group was generally much older

($t_{age}(259.74) = 26.46$, $p < .05$), had a larger proportion of Black participants in the sample ($\chi^2_{ethnicity}(1) = 13.76$, $p < .05$), and were better educated $\chi^2_{education}(6) = 141.86$, $p < .05$). These differences were to be expected because the online sample was open to any individual with access to a computer and internet connection, while the in-person sample had specifically recruited for midlife adults with a balanced sample of Black and White participants in the Chicago area. Disparities in educational attainment may be present because 37.11% of the online sample were still in college at the time of participation.

Given that the online participants who provided narratives were volunteers, tests were conducted to see whether the participants who chose to write a narrative differed from those who did not. The online participants who provided narratives ($M_{age} = 29.70$, $SD_{age} = 13.92$) were both older than those who did not ($M_{age} = 25.82$, $SD_{age} = 10.41$; $t(397.61) = 5.55$, $p < .001$ after Holm correction) and more educated ($\chi^2(6) = 31.44$, $p < .001$ after Holm correction). However, the two groups did not differ in regard to gender ($t(399.86) = 2.13$, $p =.09$) or ethnicity ($\chi^2(17) = 23.94$, $p =.12$).

Narrative linguistics: Are there significant differences in the lexical usage of words?

To determine whether word use differed across the in-person interview and online samples, a series of t-tests on 63 word categories were conducted using LIWC (Pennebaker et al., 2007). This full list of t-tests in differences of word use are provided in *Table 1*. The in-person and online samples differed on 25 of the tested word categories ($p < .05$ after Holm correction). In-person interview participants were more likely to use informal words, such as fillers (e.g., “so;” $d = -.39$, $p < .001$), non-fluencies (e.g., “um;” $d = -.31$, $p < .001$), and assents (e.g., “okay;” $d = -.28$, $p < .001$). In-person interviewees were also more likely to utilize pronouns ($d = -.15$, $p < .05$), particularly impersonal pronouns (e.g., “it;” $d = -.39$, $p < .001$) and 2nd person pronouns (e.g., “you;” $d = -.27$, $p < .001$). Lastly, in-person interviewees provided narratives containing more cognitive processing words ($d = -.23$, $p < .001$), specifically related to exclusion (e.g., “without;” $d = -.32$, $p < .001$) and tentativeness (e.g., “perhaps;” $d = -.24$, $p < .001$). In comparison, online participants were more likely to use affect words in their narratives ($d = .27$, $p < .001$), which included negative emotion (e.g., “anxiety;” $d = .20$, $p < .001$) and positive emotion words (e.g., “thankful;” $d = .15$, $p < .05$). Additionally, online participants’ narratives included more: 1st person pronouns (e.g., “I;” $d = .15$, $p < .05$); prepositions (e.g., “after;” $d = .30$, $p < .001$); articles (e.g., “the;” $d = .21$, $p < .001$); inhibition (e.g., “constrain;” $d = .16$, $p < .05$); relativity (e.g., “begin;” $d = .25$, $p < .001$); achievement (e.g., “try;” $d = .22$, $p < .001$); and work-related words (e.g., “boss;” $d = .15$, $p < .05$). Overall, the lexical content of narratives differed across collection method, where in-person interview participants tended to address the interviewer using more informal words and 2nd person pronouns, and the online participants utilized more emotion words in their typed responses. The larger utilization of cognitive processing words among in-person participants points to the possibility that they are thinking through their high and low points in more detail as they narrate them out loud. Graphical representation of word use differences between the two samples are displayed in *Figure 1*.

Insert Table 1 about here

Insert Figure 1 about here

Narrative themes: Do rates of coded redemption and contamination differ depending on collection methodology?

The next question this research examined was whether collection methodology – collecting narratives in-person versus online – yielded different probabilities of the affective narrative redemption and contamination. For these analyses, multilevel modeling with high and low points nested within each participant allowed for all narrative accounts to be utilized without inflation due to dependency (because the in-person sample provided both high and low point narratives while the online sample only provided one or the other). Narrative-specific variables were included at level 1 (i.e., redemption coding, contamination coding and word count) and person-specific variables at level 2 (i.e., age, gender, education, race, narrative collection type, and personality).

Insert Tables 2 and 3 about here

For both redemption and contamination, four models were conducted: (1) with only collection method as the predictor; (2) controlling for narrative-specific variables (i.e., whether it was a high or low point narrative and word count indicating verbosity); (3) controlling for narrative variables and demographics (i.e., age, gender, education and race); and (4) controlling for narrative variables, demographics and Big Five personality traits. These models determined whether differences in redemption and contamination coding differed across the samples because of characteristics of the participants. For clearer interpretation after model estimations, an exponential transformation was used to convert coefficients to odds ratios.

Comparing collection methodologies, narratives collected online had greater odds of containing scenes of redemption sequences than those collected in-person (M_{online} = .43, SD_{online} = .47; $M_{\text{in-person}}$ = .36, $SD_{\text{in-person}}$ = .45; OR = 1.28, 95% CI[.91, 1.78]). The effect of collection methodology was further emphasized after controlling for whether participants told a low or a high point narrative, how many words they used to tell their story, race, and personality traits (OR = 3.48, 95% CI[1.70, 7.09]). In other words, online participants were on average 248% more likely to tell a redemption story than those in the in-person interview study sample, even considering differences in narrative characteristics, demographics, and Big Five traits. Participants in the online sample also had greater odds of telling contamination stories than those in the interview sample (M_{online} = .36, SD_{online} = .42; $M_{\text{in-person}}$ = .19, $SD_{\text{in-person}}$ = .37; OR = 3.35, 95% CI[2.33, 4.81]). However, this result did not remain significant after the addition of control variables (see Model 4 in Table 3; OR = 1.94, 95% CI[0.88, 4.29]). Findings also indicated that contamination sequences were far more likely to be found in low point narratives above and beyond collection methodology, demographic, and personality trait variables (OR = 24.57, 95% CI[11.84, 50.99]).

Do the relationships between thematic variables and Big Five traits vary depending on method of narrative collection?

To examine whether the relationships between narrative-related variables and personality traits differed across collection methods, coded redemption and contamination sequences were first correlated with Big Five traits separately by sample and narrative scene (as online participants were assigned either a high or low point) and then compared using Fisher z-tests. As shown in *Table 4*, only one significant correlation was evident in the in-person sample; trait neuroticism was negatively correlated with redemption in the low point scenes (r = -.16, p < .05). For the online sample, several significant correlations were evident between the Big Five traits and redemption. In general, redemption sequences in the online participants' high point scenes were positively associated with agreeableness (r = .33, p < .05), conscientiousness (r = .29, p < .05), and extraversion (r = .13, p < .05). In the low point scenes, redemption was positively associated with agreeableness (r = .13, p < .05), extraversion (r = .18, p < .05), and openness (r = .20, p < .05). Contamination was positively associated with two personality traits during high point scenes among the online sample only – with neuroticism (r = .15, p < .05) and extraversion (r = .16, p < .05). No other significant correlations were found for contamination and personality traits during low point scenes or among participants in the in-person sample. Nevertheless, comparisons of each corresponding correlation indicated no evidence for statistically significant differences between samples. *Figure 2* also illustrates these results with overlapping confidence intervals for the in-person and online samples.

Insert Table 4 about here

Insert Figure 2 about here

Discussion

In recent years, there has been a proliferation in the use of narrative methodology – the analysis of an individual's personality through their autobiographical life stories –

within the social sciences. As technological advancements have been made in telemetric data collection methods, researchers are increasingly turning to online methods to obtain participants' narrative accounts. While the benefits of collecting psychological data using online self-report questionnaires have been well-validated (see: Gosling et al., 2004; Wilt et al., 2011), similar inquiries have not been reported for the collection of narratives online in comparison with the collection of narratives in-person with a trained interviewer. As researchers continue to study life narratives, it is integral to understand the benefits and disadvantages to using either online or in-person interviewing and assess potential discrepancies that may result from differences between the two methods. The present research is the first to make those examinations using narrative accounts from two study samples; high and low point narratives transcribed into word documents from audio-recorded, structured in-person interviews, and online, typed narratives in response to either a high or a low point prompt.

LIWC assessments on the lexical construct of the narratives indicated differences in 25 of the 63 pronoun, function, and affect word categories tested. These differences in word use may largely be due to the presence of an interviewer for the in-person sample and the absence of human interaction for the online participants. For the in-person participants, informal speech components like linguistic fillers, non-fluencies, and assents (e.g., "so," "um," and "okay") were utilized more in dialogue with an interviewer. Additionally, the in-person sample had a higher percentage of certain functional words (i.e., pronouns, verbs, adverbs, present tense, and conjugates). In comparison, the online participants were more likely to use affect words, both in the form of negative and positive emotions. Without an option to express emotions through physical gestures or paralinguistics, then, online study participants may have relied more upon explicit linguistic demonstrations of emotion. Other notable differences in narrative accounts included more 2nd person pronouns (i.e., you-words) from in-person participants and more 1st person singular pronouns (i.e., I-words) from the online sample participants. Taken in sum, these differences in word use emphasizes that something about being in the present moment in dialogue with an interviewer plays a role in how participants linguistically structure their narratives. In the presence of a listening audience, narrators may consider and narrate their life story accounts in a linguistically different way – wording stories to accommodate the present listener.

Logistic linear multilevel modeling allowed us to interpret whether differences in redemption and contamination coding differed across the samples due to participant and study characteristics. In general, narratives collected through online sampling were 248% more likely to contain redemption sequences and 94% more likely to contain contamination sequences than those collected through in-person interviews. However, only the finding for redemption sequences remained significant after controlling for type of scene (i.e., high or low point), word count, participant demographics and personality traits. One potential basis for this finding is that the anonymity of submitting personal narratives online may provide an easier or more conducive environment for individuals talking about the emotionally redemptive components of lived events. Another reason for this finding may be that in-person participants are able to rely on body language or paralinguistic tones to demonstrate redemption sequences to the interviewer. Participants in online studies, restricted to writing alone, may instead depend on more obvious textual displays of redemption sequences. The insignificant effect of collection methodology on odds of coded contamination sequences may then be due to a stronger effect of other personality traits (e.g., conscientiousness and neuroticism) and characteristics (i.e., goals and motivations) yet unmeasured. Alternatively, contamination sequences may be linguistically displayed in similar fashions regardless of collection contexts. Future research interested in narratives could consider the possibility of video-recording interviews to capture emotions or paralinguistic presentations that otherwise are absent in transcribed or audio-recorded interviews.

Notably, comparisons of each sample's correlations between personality and narrative variables showed that those relationships were generally consistent in magnitude and direction for high and low points – the correlations were not significantly different across the two methods of data collection. This was an important finding for researchers as it provides conditional support for being able to generally integrate findings regarding relationships between narrative themes and personality traits taken from narratives collected using different methodologies.

There were a few limitations to this research. The first is the low κ ratio for coded contamination. However, rates of coded contamination were in general rarer than those for redemption, therefore κ may be an underestimation of coder agreement as the ratios are affected by the prevalence of contamination sequences. Indeed, researchers have expressed concerns for κ ratios serving as an overly conservative measure of agreement (Strijbos, Martens, Prins, & Jochems, 2006; Viera & Garrett, 2005). Another limitation was low power to detect differences in correlations across the two studies. Also, the wide variation in demographic makeup of the two samples brings forth potential issues of comparability, even after controlling for demographic factors. This stems from the use of samples originally meant for other purposes rather than for explicit testing of differences between methods. As such, the present research had to rely on well-validated, but different scales for the Big Five traits. Future studies should seek to standardized demographic variables and measures across samples, and include more participants and collected narrative scenes to increase the reliability and generalizability of the results.

Scientists interested in life narratives must consider a number of key points prior to starting research, including resources for studying narratives, the population of interest, and the study's focus. First, if funding is restrained, then telemetric collection of narratives may be helpful, as online surveying does not involve scheduling of appointments and eliminates the need for a trained interviewer and subsequent transcription. Second, the Internet allows for a bigger and more diverse sample than what might be possible in-person, which could be either advantageous or disadvantageous, depending on the population of interest. Autobiographical life narratives, as a reflection of an individual's experience in their community, are inherently shaped by societal cultural norms and the individual's own socioeconomic status, race, and other identifiers (Hammack, 2008; McAdams & Manczak, 2015). Thus, if a researcher were to be interested in a specific population, geographic restrictions may be important and collection of data beyond those boundaries unnecessary. Whereas those studies interested in cross-cultural comparisons may find online methods to be more expedient; data can be collected more easily across participants in distant geographies and group settings (Gosling et al., 2004; Wilt et al., 2011). Certain populations (i.e., younger, educated, and urban-residing) may have more familiarity with online forms and may self-select into studies that utilize only online methods. Though it is also important to note that online surveys do not necessarily imply equal access to all populations (i.e., lower-income or rural populations without easy access to online services). Third, researchers must consider which method is best for their study's focus. The physical presence of a listener or interviewer and modality of narrative response (i.e., written versus verbal expression) may alter the lexical and thematic components of responses, but not necessarily the relationship between narrative themes and personality traits.

Finally, regardless of methodology, due diligence for 'quality control' must be made during collection of narrative responses. The validity of data depends largely in part on the quality of the data that studies can obtain. As an example, while a large sample was accumulated for the online sample, most participants chose not to provide a narrative response or provided very brief accounts that may have skewed the linguistic quality of their stories. Thus, it is beneficial for researchers to ensure that participants understand question items and subsequently provide meaningful answers to them (Wilt et al., 2011). For that to occur, researchers can take steps to increase the probability of collecting high quality data including: the use of clear instructions, formats which are standardized and accessible to all participants (Nosek, Banaji, & Greenwald, 2002), and websites which guide participants through the study (De Leeuw, Hox, & Kef., 2003). With in-person interviews, researchers should take care to standardize protocols to minimize any interviewer effects. During narrative interviewer training, it is essential that interviewers understand the importance of following a scripted prompt as closely as possible.

In sum, the current study delineates differences in rates of word use and coded narrative themes, but generally provides support for researchers to be able to integrate correlational findings on variables of personality traits and narrative themes acquired from online and in-person narrative methods. As methods of data collection continually improve with advancements in technology, telemetric sampling can be an innovative way for narrative researchers to expand their sampling beyond their immediate geography. Future studies examining narratives should work to disseminate the differences (or similarities) between telemetric and in-person studies. This can be done by either (1) specifically guiding telemetrically-sampled participants through the narrative process to ensure that adequate data is collected for between-sample comparisons, (2) allowing for encoded voice transcriptions for a more comparable analysis between traditional in-person narrative and online collection methods, or (3) working with researchers using telemetric methods to standardize narrative assessment prompts across studies.

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678 Tables

Table 1

T-tests of differences in word use between interview and online samples

Word category	In-person sample mean	Online sample mean	Standardized difference	*t*-value	*p*-value	Adjusted *p*-value
Word count	699.29	250.92	-0.32	-7.41	0	0
Informal speech						
Fillers	2.63	0.12	-0.39	-9.01	0	0
Nonfluencies	1.46	0.07	-0.31	-7.32	0	0
Assent	0.72	0.07	-0.28	-6.45	0	0
Pronouns	21.49	19.14	-0.15	-3.54	0	0.02
Impersonal pronouns	8.08	4.99	-0.39	-9.01	0	0
Personal pronouns	13.47	14.17	0.05	1.22	0.22	1
2nd person (e.g., “you”)	1.02	0.19	-0.27	-6.27	0	0
1st person sing. (e.g., “I”)	8.64	10.26	0.15	3.4	0.001	0.03
3rd person pl. (e.g., “they”)	0.8	0.47	-0.12	-2.75	0.01	0.19
1st person pl. (e.g., “we”)	0.8	1.14	0.08	1.9	0.06	1
3rd person sing. (e.g., “she”)	2.29	2.13	-0.02	-0.47	0.64	1
Function words	63.65	60.36	-0.11	-2.46	0.01	0.39
Common adverbs	6.89	4.46	-0.32	-7.49	0	0
Present tense	7.22	4.27	-0.3	-7.03	0	0
Prepositions	10.7	13.46	0.3	7.02	0	0
Auxiliary verb	11.39	8.88	-0.28	-6.64	0	0
Conjunctions	9.31	7.25	-0.27	-6.24	0	0
Articles	4.82	6.28	0.21	5	0	0
Regular verbs	17.35	14.88	-0.21	-4.84	0	0
Negations	2.13	1.62	-0.13	-3.1	0.002	0.07
Numbers	1.1	0.93	-0.06	-1.37	0.17	1
Past tense	8.37	8.86	0.05	1.16	0.25	1
Future tense	0.68	0.59	-0.04	-1.02	0.31	1
Quantifiers	2.28	2.11	-0.04	-0.95	0.34	1
Affect words	4.19	6.13	0.27	6.26	0	0
Negative emotion	1.69	2.76	0.2	4.61	0	0
Anxiety	0.32	0.72	0.15	3.42	0.001	0.03
Anger	0.3	0.59	0.13	2.96	0.003	0.1
Sad	0.57	0.91	0.11	2.59	0.01	0.3
Positive emotion	2.44	3.33	0.15	3.6	0	0.01

Word category		In-person sample mean	Online sample mean	Standardized difference	*t*-value	*p*-value	Adjusted *p*-value
Social Words		9.8	9.52	-0.02	-0.44	0.66	1
	Family	1.13	1.44	0.07	1.61	0.11	1
	Humans	0.95	0.89	-0.02	-0.46	0.65	1
	Friends	0.3	0.32	0.01	0.2	0.84	1
Cognitive processes		19.43	16.27	-0.23	-5.43	0	0
	Exclusive	3.71	2.03	-0.32	-7.46	0	0
	Tentativeness	2.74	1.62	-0.24	-5.58	0	0
	Inhibition	0.27	0.53	0.16	3.69	0	0.01
	Certainty	1.58	1.23	-0.1	-2.38	0.02	0.47
	Inclusive	6.62	6	-0.08	-1.91	0.06	1
	Causation	1.46	1.54	0.02	0.56	0.57	1
	Insight	2.71	2.65	-0.01	-0.24	0.81	1
Perceptual processes		1.98	2.24	0.05	1.27	0.2	1
	Feel	0.6	0.9	0.11	2.63	0.01	0.27
	Hear	0.85	0.56	-0.11	-2.48	0.01	0.38
	See	0.47	0.61	0.06	1.48	0.14	1
Biological processes		1.5	2.16	0.13	3.14	0.002	0.06
	Body	0.3	0.54	0.1	2.22	0.03	0.67
	Sexuality	0.16	0.32	0.09	2.09	0.04	0.88
	Health/illness	0.89	1.09	0.06	1.28	0.2	1
	Ingesting	0.21	0.25	0.03	0.61	0.54	1
Relativity		12.52	15.69	0.25	5.81	0	0
	Time	5.5	6.55	0.14	3.2	0.001	0.05
	Space	5.48	6.49	0.13	3.11	0.002	0.07
	Motion	2.05	2.48	0.1	2.23	0.02	0.52
Personal concerns							
	Achievement	1.12	2.03	0.22	5.07	0	0
	Work	1.28	2.29	0.15	3.5	0	0.02
	Money	0.21	0.51	0.13	3.05	0.002	0.08
	Leisure	0.6	0.99	0.11	2.59	0.01	0.3
	Home	0.56	0.8	0.09	2.01	0.04	1
	Death	0.29	0.23	-0.03	-0.68	0.5	1
	Religion	0.28	0.25	-0.01	-0.22	0.82	1

Note: Items are listed under their respective word categories in order from biggest to smallest *t*-value. The p-values for the t-tests were adjusted using a Holm correction.

Table 2

Differences in odds of coded Redemption Sequences (RS)

	(1)	(2)	(3)	(4)
Constant	0.73*	0.40*	0.09*	0.16*
	[0.58, 0.91]	[0.26, 0.61]	[0.03, 0.31]	[0.04, 0.58]
Online sample	1.28	2.14*	4.22*	3.48*
	[0.91, 1.78]	[1.40, 3.27]	[2.10, 8.47]	[1.70, 7.09]
Difference between low & high point		0.80	0.84	0.85
		[0.56, 1.14]	[0.58, 1.22]	[0.58, 1.24]
Word count		1.00*	1.00*	1.00*
		[1.00, 1.00]	[1.00, 1.00]	[1.00, 1.00]
Age			1.03*	1.03*
			[1.01, 1.06]	[1.00, 1.05]
Sex			1.05	1.04
			[0.73, 1.52]	[0.71, 1.54]
Education			0.95	0.91
			[0.85, 1.07]	[0.81, 1.03]
Race			1.03	1.10
			[0.71, 1.50]	[0.74, 1.63]
Extraversion				1.05
				[0.86, 1.29]
Agreeableness				1.09
				[0.90, 1.33]
Conscientiousness				1.24*
				[1.02, 1.50]
Neuroticism				0.90
				[0.73, 1.12]
Openness				1.11
				[0.92, 1.35]
Observations	570	570	536	521
Log Likelihood	-390.90	-382.07	-355.77	-339.52
Akaike Inf. Crit.	787.80	774.13	729.54	707.04
Bayesian Inf. Crit.	800.84	795.86	768.10	766.62

Note: $^{*}p < .05$
Personality and education were standardized within samples.
Numbers in brackets [ ] are values for 95% confidence intervals.

Table 3

Differences in odds of coded Contamination Sequences (CS)

	(1)	(2)	(3)	(4)
Constant	0.28*	0.03*	0.07*	0.07*
	[0.21, 0.36]	[0.01, 0.06]	[0.01, 0.30]	[0.01, 0.32]
Online sample	3.35*	2.84*	1.80	1.94
	[2.33, 4.81]	[1.70, 4.74]	[0.83, 3.89]	[0.88, 4.29]
Difference between low & high point		21.81*	23.97*	24.57*
		[11.06, 43.02]	[11.64, 49.37]	[11.84, 50.99]
Word count		1.00	1.00	1.00
		[1.00, 1.00]	[1.00, 1.00]	[1.00, 1.00]
Age			0.97*	0.97*
			[0.95, 1.00]	[0.95, 1.00]
Sex			1.07	0.93
			[0.65, 1.70]	[0.57, 1.52]
Education			1.09	1.11
			[0.94, 1.26]	[0.95, 1.29]
Race			0.96	0.87
			[0.60, 1.55]	[0.67, 1.12]
Extraversion				0.87
				[0.67, 1.12]
Agreeableness				0.96
				[0.75, 1.22]
Conscientiousness				1.37*
				[1.07, 1.75]
Neuroticism				1.30*
				[1.00, 1.69]
Openness				1.16
				[0.91, 1.48]
Observations	570	570	536	521
Log Likelihood	-341.32	-266.97	-245.36	-233.27
Akaike Inf. Crit.	688.64	543.93	508.73	494.53
Bayesian Inf. Crit.	701.68	565.66	547.28	554.11

Note: $*p < .05$
Personality and education were standardized within samples.
Numbers in brackets [ ] are values for 95% confidence intervals.

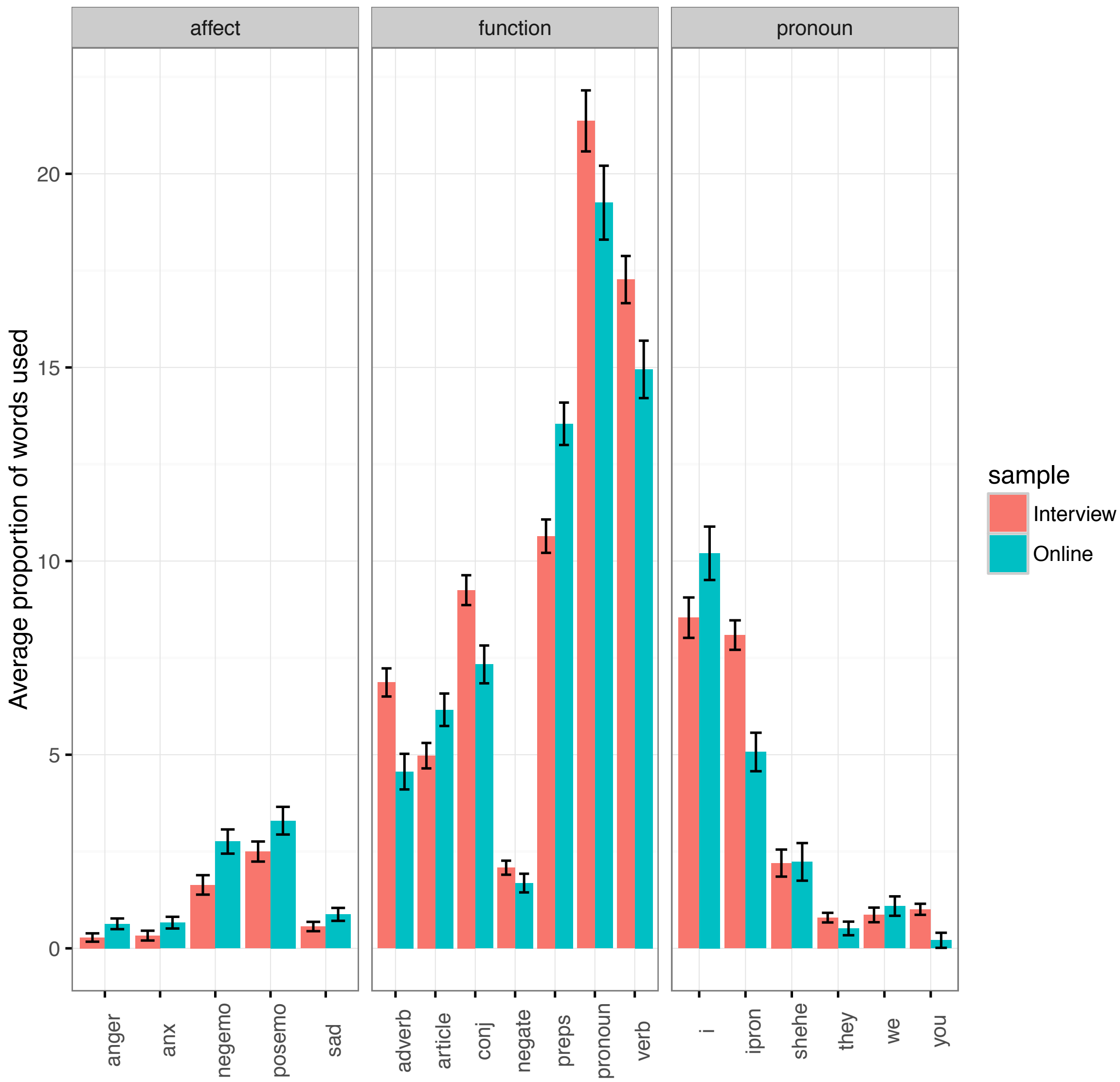
Table 4

Differences in correlations found in high and low point stories

Variable 1	Variable 2	High or low point	In-person *r*	Online *r*	*z*-statistic	*p*-value	adjusted *p*-value
Agreeableness	Contamination	high	-0.04	0.08	-0.83	0.41	1.00
Agreeableness	Contamination	low	-0.09	-0.03	-0.55	0.58	1.00
Agreeableness	Redemption	high	0.06	**0.33***	-1.94	0.05	1.00
Agreeableness	Redemption	low	0.10	**0.13***	-0.28	0.78	1.00
Conscientiousness	Contamination	high	0.06	0.10	-0.28	0.78	1.00
Conscientiousness	Contamination	low	0.10	0.04	0.55	0.58	1.00
Conscientiousness	Redemption	high	0.06	**0.29***	-1.64	0.10	1.00
Conscientiousness	Redemption	low	0.13	0.07	0.55	0.58	1.00
Extraversion	Contamination	high	-0.09	**0.16***	-1.72	0.09	1.00
Extraversion	Contamination	low	-0.03	-0.08	0.45	0.65	1.00
Extraversion	Redemption	high	0.07	**0.13***	-0.42	0.68	1.00
Extraversion	Redemption	low	0.07	**0.18***	-1.01	0.31	1.00
Neuroticism	Contamination	high	0.03	**0.15***	-0.82	0.41	1.00
Neuroticism	Contamination	low	0.14	0.03	1.01	0.31	1.00
Neuroticism	Redemption	high	-0.04	-0.02	-0.14	0.89	1.00
Neuroticism	Redemption	low	**-0.16***	-0.06	-0.92	0.36	1.00
Openness	Contamination	high	-0.05	-0.07	0.14	0.89	1.00
Openness	Contamination	low	0.03	0.08	-0.46	0.65	1.00
Openness	Redemption	high	-0.05	0.07	-0.82	0.41	1.00
Openness	Redemption	low	0.00	**0.20***	-1.84	0.07	1.00

Note: * $p < .05$
Correlations are corrected for multiple comparisons

Figures



Note: anx = anxiety words, negemo = negative emotion, posemo = positive emotion, conj = conjunction, negate = negations, preps = prepositions, i = first person singular pronouns, ipron = indefinite pronouns, shehe = third person singular pronouns.

Figure 1. Word use by sample, with 95% confidence intervals

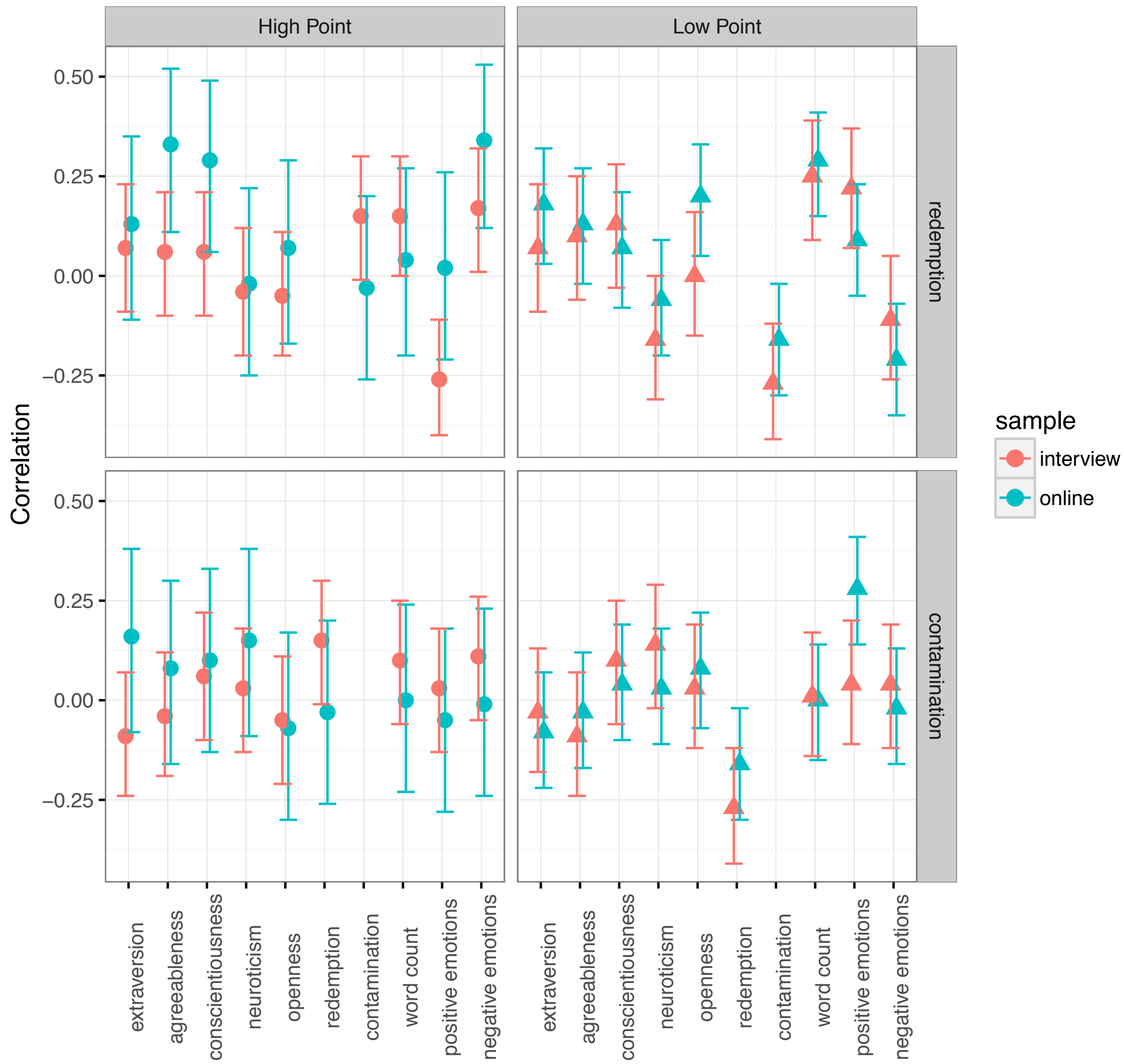


Figure 2. Correlations between Big Five personality traits and redemption and contamination sequences.

Appendix A

The Structured Life Story Interview (high and low points only)
Revised February 2008, McAdams, D.P.
For use at the Foley Center for the Study of Lives, Northwestern University

1. High point: Please describe a scene, episode, or moment in your life that stands out as an especially positive experience. This might be the high point scene of your entire life, or else an especially happy, joyous, exciting, or wonderful moment in the story. Please describe this high point scene in detail. What happened, when and where, who was involved, and what were you thinking and feeling? Also, please say a word or two about why you think this particular moment was so good and what the scene may say about who you are as a person.

2. Low point: The second scene is the opposite of the first. Thinking back over your entire life, please identify a scene that stands out as a low point, if not the low point in your life story. Even though this event is unpleasant, I would appreciate your providing as much detail as you can about it. What happened in the event, where and when, who was involved, and what were you thinking and feeling? Also, please say a word or two about why you think this particular moment was so bad and what the scene may say about you or your life.