Finding Emergent Collaborative Structures: Wearable Sensors and Advanced Data Analytics

by

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Over the last two decades, technology enterprises have continuously shifted the internal design of their R&D operations from bureaucratic structures as a means of facilitating knowledge transfer among employees towards networked, team-based configurations. In their efforts "to make large companies feel small", these organizations have traded relatively stable, hierarchical functional units for more fluid, non-hierarchical networked teams. In such non-hierarchical settings, mutual adjustment is the primary coordination mechanism and knowledge exchange is primarily realized in emergent rather than planned structures. Despite their practical relevance, little is known about the dynamics of emergent collaborative structures.

Recent technological advances have created unprecedented opportunities to study the complex interplay between collaborative dynamics and organizational structure. One such opportunity derives from the ability to capture granular, relational data through low-cost wearable sensor technology. The data streams from these devices can shed light on the periodicity, duration, composition, and operational details of emergent organizational structures.

In this research, I sought to study the structural dynamics of non-hierarchical organizations. More specifically, I explored the question of how emergent collaborative structures within teams might affect knowledge flow and performance over time. This was done in the context of a laboratory experiment simulating a collaborative project with resources limitations, knowledge transfer needs, success metrics, and ambiguous project paths. My results suggest that emergent collaborative structures in non-hierarchical teams (1) change over time and (2) can be identified and characterized by employing advanced data analysis techniques to wearable-sensor derived proximity data. Thus, my research contributes to the literature on collaborative dynamics within organizations.

Acknowledgements

I would like to thank Ralph A. Heidl, Associate Professor of Management for serving as my primary advisor and going above and beyond in helping me fully examine the topic of emergent collaborative structures and consider the impact wearable sensors and various technology can have on individuals, teams, and organizations. His support, guidance, subject matter expertise, and academic writing prowess were invaluable throughout this lengthy process. More importantly, despite many setbacks and pivots, Professor Heidl was steadfast in his commitment to this project and made working with him a pleasure. He was thoughtful, understanding, and all too importantly, funny. I truly could not have completed this thesis without him.

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Lastly, to my mother, father, and two sisters, I extend my deepest thanks and gratitude. All that I am, have done, and will do, are because of you.

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Introduction / Chapter 1: Wearable Devices and Collaboration

Regardless of industry, the mutual understanding and sharing of knowledge is a critical factor of success in the professional world. More specifically, individual and team success hinges on the ability to collaborate, disseminate information, and solve ambiguous problems. Furthermore, the actual structure and composition of an organizational collective directly influences the degree to which collaboration and knowledge transfer occurs. In effect, each organization's structure also impacts the organization's knowledge network, which is a "set of nodes interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge" (Phelps et al. 2012). There is a plethora of research that supports the notion of knowledge networks within organizations influencing how valuable information is shared and diffused (e.g., Phelps et al, 2012; Brennecke & Rank, 2016). Thus, since the inception of modern business, organizations have sought to adopt structures to improve coordination and knowledge sharing.

Organizations rely on formal structures to facilitate interactions between subsets of employees. Traditionally, business organizations have used hierarchical structures—where most entities within the business are subordinate to one, or multiple other entities—to maintain stability and impose pathways for communication (Lee, 2016). While these configurations tend to be more rigid, centralized, and organized, they can cause conflict over resource use, create information bottlenecks, and incite personnel issues. The 2007 paper, "Organization at the Leading Edge: Introducing Holacracy", by Brian J. Robertson, states, "even at its best [hierarchy] tends to be inflexible to change and ill-equipped to artfully navigate the complexity most businesses navigate today."

Unsurprisingly, hierarchies are still the prevailing organizational structure, but over the last decade, non-hierarchical models have become more popular as real-world organizations adopt more flexible structures.

However, non-hierarchical modes of organizing appear to be producing mixed results with respect to performance. Many companies have made the leap to non-hierarchical organizational structure, including Zappos, a multi-billion-dollar retail company. Some businesses have adopted these flatter and less rigid structures for their flexibility and responsiveness, enabling employees to take advantage of all of their skills, rather than restricting themselves to the limited skill set anchored in their job title (Yale Insights, 2018). However, these benefits do not come without a cost. The cost of non-hierarchical organizing relates to the additional coordination that needs to be performed by individuals in the absence of formal authority relationships (Kastelle 2013). Zappos, for example, had significant issues with confusion and overworking. *The Atlantic* reported, “self-governing produced a bit of a mess, with some workers telling reporters that they weren’t sure how to get things done anymore” (Lam, 2016).

Despite these setbacks, non-hierarchical organizing of complex work tasks has become the norm, rather than the exception. Prior research supports the notion that non-hierarchical structures cause front-loaded coordination costs that result in knowledge exchange inefficiencies that dampen initial performance (Phelps, 2012). Communication pathways become oversaturated because there is not a structure to guide them. Thus, extant literature suggests that, as employees begin to mutually adjust and understand who has relevant information and who possesses key skills, collective performance may be hampered. However, over time coordination improves and the benefits provided by non-hierarchical structures should begin to outweigh these costs (Heidl, 2017). See Figure 1.

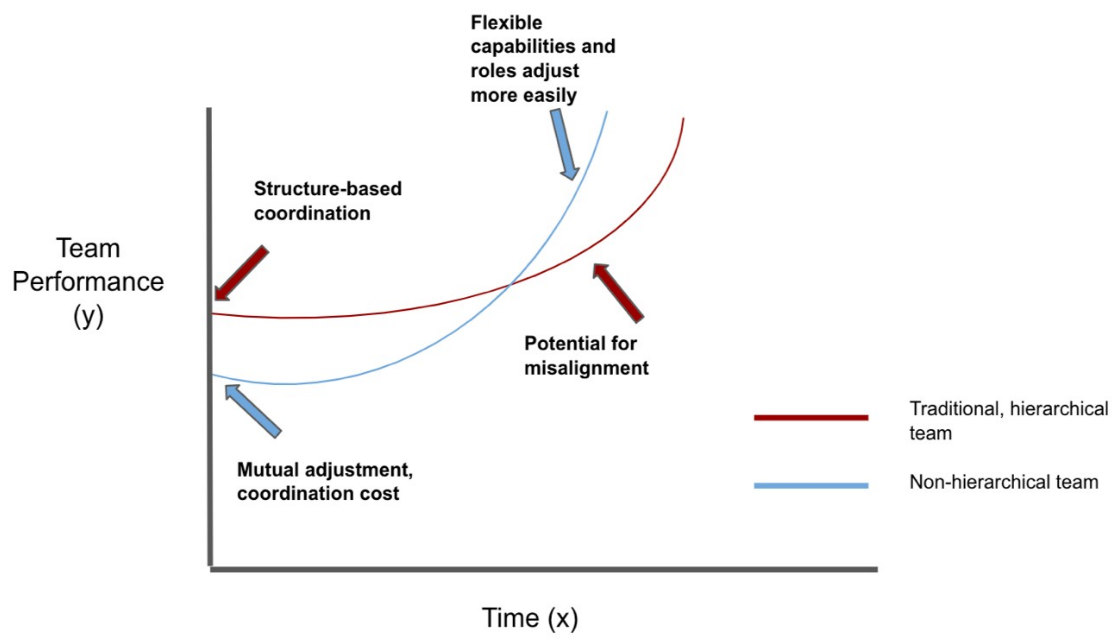


Figure 1: A depiction of the mutual adjustment costs that non-hierarchical teams undergo initially, plus the eventual benefits teams receive from flexibility and better resource allocation.

Historically, the effects of non-hierarchical structure on collective performance and communication has almost entirely been measured and studied using surveys and interviews. Although this research has yielded valuable insights, survey-based methods are cumbersome, costly, and ill-suited to capture data reflective of the structural dynamics of non-hierarchical teams (McDonald, 2019). Because of the prohibitive costs associated with the collection of granular relational data, organizational research has been unable to produce the empirical data to effectively examine the dynamics of emergent collaborative structures. However, with the advent of low-cost wearable sensors, organizational researchers now can collect temporal, relational data for larger numbers of subjects. These data provide the means to begin to unpack the micro-processes driving the costs and benefits of knowledge exchange and emergent collaborative dynamics in unstructured organizations (McDonald, 2019).

Specifically, wearable proximity sensors allow for the collection of fine-granular interaction data over a given period of time (Chaffin et al, 2017). Wearable sensor technology is quickly becoming a mainstream development in prominent companies to locate people and monitor their movements (*Economist,* 2019). GPS tracking through employee IDs, email monitoring, and wellness programs are some of many ways that companies already collect employee information (Jagannathan, 2019). The full set of costs and benefits of these developments have yet to emerge, but this study offers a unique opportunity to explore how wearable sensors could be used to increase productivity, collaboration, and knowledge transfer in team-based organizations. Furthermore, because the use of Bluetooth sensors in network emergence research is relatively new, this research illustrates a meaningful expansion of our methodological approach towards analyzing wearable sensor data.

This research also relies on a novel analytical approach for identifying regularities in complex relational data. Using tensor decomposition, we show how continuous data depicting colocation (proximity) relationships can be leveraged to identify and classify emergent collaborative dynamics in space and time. The present research represents a first step towards developing a novel perspective on the crossroads of emergent collaborative structures, organizational design, and knowledge networks. In the following sections, I will develop the theoretical framework for this research, outline my research and methodology, and discuss the data analysis and results. I will conclude with a discussion about future applications of my research and what further research is needed given the limitations of this study.

Chapter 2: Theoretical Framework

In 1987, J. Richard Hackman published "The Design of Work Teams", which to this day, is still an important body of work in organizational design. Hackman wrote, "the design of a group…should promote effective task behavior and lessen the chances that members will encounter built-in obstacles to good performance." Historically, creating vertical hierarchies has been the most common way for organizations to enable good performance because this structure promotes company-wide coordination with very rigid knowledge networks and predisposed communication pathways (Walsh, 2017). In a large organization, coordination between department heads, managers, and C-suite officers is critical for decision-making. However, the value of a vertical hierarchy can potentially be limited if senior managers become overloaded with information, causing important decision-making to become entangled (Rishipal, 2014). The usefulness of a vertical hierarchy further declines when "the competence of subordinates rises…so it becomes feasible to widen spans of control and to reduce levels of management" (Rivkin, 2003).

Ten years after the Rivkin paper was published, Zappos began transitioning to a self-managing holacracy model. As the number of fast-paced, tech, and data-driven companies like Zappos continues to increase, a noteworthy shift is occurring. The traditional pillars of predictability, standardization, and formalization in vertical hierarchies have given way to more malleable and dynamic non-hierarchical structures (Bernstein, 2016). Companies are beginning to use non-hierarchical structures to provide flexibility—both externally to market and consumers shifts, as well as internally for optimal use of relevant skills, resources, and networks. In fast-paced environments, tension between flexibility and reliability has been a long-standing concern—specifically for tech companies and their organizational design (Borkar, 2010). To keep up with dynamic external environments, many organizations have transitioned to a less hierarchical structure to allow for robust knowledge-sharing capabilities in their networks (Kastelle, 2013).

Extant research has long recognized that knowledge networks, created from the networks of social relationships, have a substantial influence on the "process of knowledge creation, diffusion, absorption, and use" (Phelps et al. 2010). Furthermore, the ability for an organization to quickly and efficiently create, absorb, and use relevant information is critical for success. While the paper titled "Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda" provides one of the first systematic reviews of knowledge network research—furthering the body of research on knowledge creation and transfer— it also provides a road map identifying future work to be done on this topic, particularly in relation to organizational structure.

Within this study, I propose that non-hierarchical design gives rise to emergent structures, which rely heavily on mutual adjustment as a coordination mechanism. Mutual adjustment is a time-consuming mode for coordinating the activities within a collective of individuals. Relative to hierarchical structures, non-hierarchical organizing may produce an initial performance disadvantage. However, over time, dynamics and performance are expected to improve due to the added benefit of improved resource allocation and flexibility (Iliadou, et al., 2018). These benefits are more pronounced in environments that are subject to uncertainty due to rapid technological change (Velinov et al., 2018). This is the reason why many technology enterprises have moved away from more bureaucratic hierarchical designs in favor of non-hierarchical organizational forms. However, due to methodological constraints, research that has examined the emergent collaborative processes and the structures that determine when and how the benefits of non-hierarchical organizing materialize is scarce. With new technology and methodological capabilities, there now exists the opportunity to study the dynamic in non-hierarchical organizations.

Collaborative dynamics reflected as the interactions among individuals consist of the unconscious, psychological forces that influence an organization's ability, behavior, and overall performance (Belker, 2019). Today's businesses operate as team-based networked organizations, which is why teams represent important resources for knowledge creation and integration (Rosendaal, 2009). Because of their obligation and liability within the context of their organizations, teams can be an incubator for knowledge creation and sharing. Task-focus, team composition, synergy, and resource overload are some of many characteristics that enable teams to have adequate resources and information when operating (Rosendaal, 2009). Thus, it is this structure that enables teams to provide ample knowledge creation and sharing, which can lead to greater organizational performance through improvements to an organization's products, services, and processes (Tsai, 2001).

However, the granular, relational data-streams—coupled with novel tensor decomposition data analytics—that low-cost wearable sensors provide offer ample opportunity to further our understanding of this topic.

Wearable sensors have become a central component for healthcare and lifestyle applications (Pentland, 2004). However, certain types of wearable sensors have great utility for identifying emergent collaborative structures. This is possible because wearable sensors can capture interaction data for a large number of individuals over extended periods of time at a relatively low cost. Together with advanced data analytic procedures such as tensor decomposition, wearable sensor generated relational data streams provide a means for overcoming previous methodological obstacles to studying emergent collaborative structures.

Chapter 3: Methodology and Results

Overview

Because of the technological novelty of the tools used for collecting data on emergent collaborative structures and dynamics, and the exploratory nature of the study, I chose an experimental research design. The advantage of an experiment is the control the researcher has varying potential disturbances due to environmental conditions. This was particularly important in the context of wearable sensors to avoid extraneous factors influencing the quality of the proximity data. Spatial obstacles, like cubicles, for example, can impact opportunities for knowledge exchange and collaboration, while wearable sensor data would indicate close proximity situations.

To effectively identify and observe emergent structures and their connection with knowledge networks and collaborative dynamics, I developed a collaborative exercise that would simulate a real-world task environment. I then randomly assigned participants to hierarchical and non-hierarchical conditions. Each experiment was comprised of 7 individuals each (21 total participants). The hierarchical condition had a designated ‘project manager’ with the rest of the group taking on the subordinate role, whereas the non-hierarchical condition was not given any instructions as to their positions, titles, or experience. I had participants fill out a pre-task survey and post-task survey, while also video recording each team session. Lastly, each participant was fitted with a wearable sensor to record spatial separation and proximity from other participants and workstations.

Research Population and Recruitment

The participant population for this experiment was comprised of University of Oregon students aged 18 – 22 years old, selected from undergraduate and graduate courses in the Lundquist College of Business. Careful consideration was placed on recruiting students with a mix of gender and racial diversification, but all materials and instructions were given in English. Students recruited from courses were offered extra credit to participate in this study. To ensure unbiased participation and compliance with Institutional Review Board (IRB) standards, those students were also offered an alternative assignment by their professor(s) if they did not have any interest in participating in the study. Both options were of equal value towards their class performance. We complied with all IRB requirements and standards to ensure research participants were protected and supported throughout the research period and that all research members responsibly carried out the research. Additionally, Amazon gift cards were offered to the winning group as an extra incentive to participate. The moderator received verbal consent from each participant before starting the activity, and also received written consent within the pre-survey that each participant took.

Task Design and Implementation

Work groups typically deal with fast-paced, ambiguous, constantly changing environments when challenged with a project. Each member has different skills, experience, and communication preferences that they lean on throughout a project's duration (Bernstein, 2016). In traditional hierarchical teams with a project manager, for example, knowledge diffusion typically relies on top, down communication. Communication pathways are prescribed, and coordination can become difficult in complex situations (Walsh, 2017). Conversely, non-hierarchical organized work groups can potentially take advantage of their flexibility and flatness by leveraging everyone's experience and skills. However, it may initially take time to identify who is useful in what capacity (Iliadou, et al., 2018). Thus, while all groups were given identical sets of instructions for the collaborative exercise, we randomly assigned a 'project manager' for the hierarchical condition, to coordinate participant's activities. Conversely, in the non-hierarchical condition, participants were not given titles or any structure, so we could observe how they organized themselves.

To incentivize the development of emergent collaborative structures, I designed a tower building exercise using magnetic components and connectors, to be constructed. The groups were also given a time limit of 45 minutes (See accompanying material 1 for instructions example). Specific care was taken to reduce the number of pieces allocated to each team in order to mimic resource constraints in real life (see Figure 2).

Figure 2: Magnetic pieces and balls laid out for participants, including the set of instructions (on left) for building the complete tower.

Furthermore, the task was comprised of three different component pieces—4 identical legs, a middle platform, and a tower—with an integration phase needed at the very end to bring each individual piece together. This design was informed by the reality of many new product development projects operating in technology firms. In this context, project members are tasked to find solutions to complex problems. Members oscillate between different configurations where some component tasks are accomplished individually or in small groups, while others require all project members to come together to produce the final deliverable.

With time and resource constraints, real-life projects often struggle in aligning their collaborative structure with the demands of the different task components (Roger, et al. 2017). A non-hierarchical structure typically frontloads coordination costs, as project members need to mutually adjust to each other to establish roles and responsibilities. In fast-paced, high-tech business settings, software development units often break up into smaller groups to work on smaller phases of projects before they integrate all their work at once to save resources and time (Linda, Janoff, 2000). I designed the tower in a similar fashion, to catalyze some of these coordination costs, so we could use our sensors and video logs to observe the emergent collaborative performance over time. Each piece of the full tower is photographed in the appendix.

Multi-Method Approach

Capturing emergent collaborative structures involved wearable sensors, primarily, as well as surveys and video analysis to validate that what the wearable sensor data and tensor decomposition showed us was exactly what happened. To properly collect proximity data with the wearable sensors, a sensor was attached to each participant, and one was placed on each table to record when participants were clustered around certain workstations and the resource center. All magnets and materials were placed on the resource table in the center of the room, then three designated workstations were created around the table in a triangle format to promote spatial separation. We anticipated participants to work individually or in small groups to construct each part of the tower. Finally, I expected them to come together to integrate the pieces at one workstation. Our sensors placed at each station helped to capture these dynamics (see Figures 3 and 4).

Figure 3: The wearable devices that were distributed to each participant.

	A	B	C
1	time	device	rssi
2	7/22/19 10:46	4101	-60
3	7/22/19 10:46	3456	-63
4	7/22/19 10:46	7460	-63
5	7/22/19 10:46	3452	-64
6	7/22/19 10:46	6719	-64
7	7/22/19 10:46	6296	-67
8	7/22/19 10:46	919	-68
9	7/22/19 10:46	1738	-70
10	7/22/19 10:46	6959	-71
11	7/22/19 10:46	8610	-71
12	7/22/19 10:46	7807	-83
13	7/22/19 10:46	7807	-59
14	7/22/19 10:46	3452	-61
15	7/22/19 10:46	4101	-62

Figure 4: Raw wearable sensor data.

Figure 4 shows an example of raw sensor data without tensor decomposition. It includes the time stamp, which sends pulses out to other sensors every 10 seconds, as well as the device symbol and Radio Signal Strength Indicator (rssi)—which indicates the sensors' proximity relative to other sensors.

In order to find emergent collaborative structures in our study we converted the wearable sensor data into a tensor (See Figure 5 for an example) (McDonald, 2019). A tensor is essentially a multidimensional array of data. Tensors are widely used in data mining, neuroscience, signal processing, and graph analysis, among other data-heavy fields. Tensors with three or more orders, like ours, are considered higher order tensors (Kolda, Bader, 2009). Because the data we captured were multidimensional, tensor decomposition represents a useful data reduction method to visualize emergent collaborative structures.

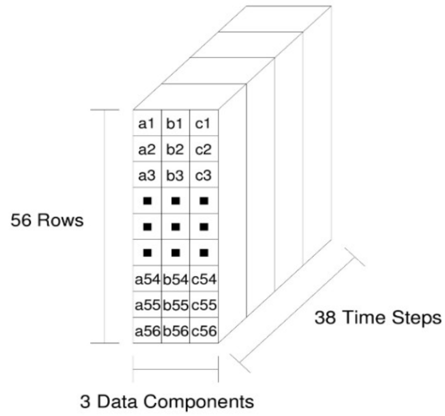


Figure 5: The data is arranged in a 3-dimensional arrangement in order to perform tensor decomposition.

Our three dimensions of data included the relation between wearable sensors (the dyad e.g. A and B, C and A), the sensors' proximity to each other sensor (dyad strength), and the time that each sensor was communicating with the others. By giving each data component a 'weight'—given its strength of tie relative to other sensors—the loadings of each data component can be entered into a tensor minimization algorithm that translates each data component—the dyads, dyad strength, and duration—into a complex relationship network.

After recording and analyzing the sensor data, we shifted focus to our survey data. Just like traditional studies on organizational structure and team performance, we created and distributed surveys to collect specific information both before the experiment and after. The pre-survey was created to identify general demographic information, if participants had prior relationships with any other participants, their general communication patterns, and their expressed written consent. Ideally, with a much larger sample size, if there was any indication of prior contact between participants, we would be able to figure that into our analysis of collaboration between associated participants. However, with the sample size we had, the survey data was not figured into our conclusion of emergent structures in differently organized teams. Instead, we utilized our extensive video data as validation for our wearable sensor data.

Our video recordings allowed me to visually observe the emergent collaborative structures as participants worked through the task at hand. Comparing the times, I was able to monitors progression through the given set of instructions, as well as their collaborative progress. I devised our experimental design so that we could use the video sequences to observe multiple performance markers. We would expect the non-hierarchical team to take on an initial coordination penalty but outperform the hierarchical team in the long run. While we were able to quantitatively observe part of this performance dynamic despite our small sample size, much additional research is needed to expand the empirical base for a statistically meaningful analysis of performance outcomes related to specific emergent collaborative structures. Despite this, the video logs represent a tangible verification that our tensor decomposition accurately visualized the extent of collaboration and communication within each team.

This study projects a significant opportunity for organizational research. However, there are important limitations in the present research design and execution. Due to time and resource constraints, I was only able to perform one research session with 3 teams total. Ideally, at least 6 more months would be needed to conduct enough sessions and obtain a sample big enough to analyze and determine the differences between different emergent structures, and how to tie those structures to team performance using wearable sensors and tensor decomposition.

Furthermore, with only one instance of hierarchical condition in our data set, it is impossible to draw conclusions about their performance within our experiment. While the hierarchical condition resulted in inferior performance relative to the non-hierarchical team—as expected—it is impossible to attribute the difference to organizational design. A larger sample size (i.e. 200 instances) would be needed to enable meaningful statistical analyses. Bias was also introduced into the dataset by individuals who had childhood experience with magnetic toys who had a much easier time understanding how certain structures could be built using the materials. Despite these limitations, our exploratory effort showed the importance and robustness of wearable sensors as a practical piece of technology in organizational design and emergent structure analysis. We have continued data collection throughout the process of drafting this thesis with the intention of publishing our work in an academy of management learning journal to illustrate the benefits of our designed exercise, coupled with our application of wearable sensors.

Chapter 4: Results and Data Analysis

Extant research has associated employee and organizational performance with the ability to individually and collectively solve complex, ambiguous problems using limited information (O'Connor, et al., 2017). The structure and composition of work groups has been shown to influence the type of collaboration needed to be successful in fast-paced, dynamic environments (Diefenbach, Sillince, 2011). Historically, businesses have used structured, hierarchical organizing to achieve efficiency and scalability in relatively stable environments. The performance trade-off associated with hierarchical organizations is well understood. In unstable, dynamic environments non-hierarchical organizing is expected to yield superior performance. However, our knowledge of when and how these benefits materialize is incomplete. In this study, we employ wearable sensors to examine how non-hierarchical organizing influences collaboration and knowledge-transfer in team-based organizations. Applying a novel analytical approach to wearable sensor data, we are able to provide a first glimpse at the connection between emergent collaborative structures, organizational design, and knowledge networks.

In the context of an exploratory experimental design, the results of my research come from a reduced sample of data. Nevertheless, I am able to identify and visualize emergent structures underlying the collaborative dynamics in a non-hierarchical team. These initial insights are promising because our findings are based on an experimental design, which closely resembles many aspects of real-life projects and the work environments in which they function. My original intuition was that hierarchical organizations would have initial benefits from a structured form of communication and leadership, but would incur penalties later due to misallocation of talent and resources driven by organizational rigidity. In fact, our one hierarchical instance of the experiment did exhibit some of these exact tendencies, completing the collaborative exercise much slower than their non-hierarchical counterparts.

The most promising result from my research came from observing a particular non-hierarchical instance of the experiment. Under this condition, the participants completed the tower exercise faster than any other team. With no formalized structure or prescribed communication pathways, as anticipated, they initially were slow and cumbersome engaging with the exercise. After several minutes, participants coordinated and organized themselves into smaller work groups to complete each phase of the tower, replicating the successful work of others in their group. They were able to successfully replicate the 4 legs of the building, the middle piece, and the tower phase in small groups, then regrouped to integrate the 3 separate phases (see Figures 6 and 7). Using tensor decomposition, we were able to quantitatively identify these emergent structures from the wearable sensors-produced data streams. Thus, tensor decomposition enabled the identification of regularities in multidimensional data. Tensor components represents the data regularities produced by emergent collaborative structures. We can transform the quantitative properties of tensor components into networks of colocation and collaborative configurations for visualization purposes (see figure 7).[1]

[1] The tensor decomposition throughout this entire project was exclusively performed by Aaron McDonald, the second reader on my thesis defense committee.

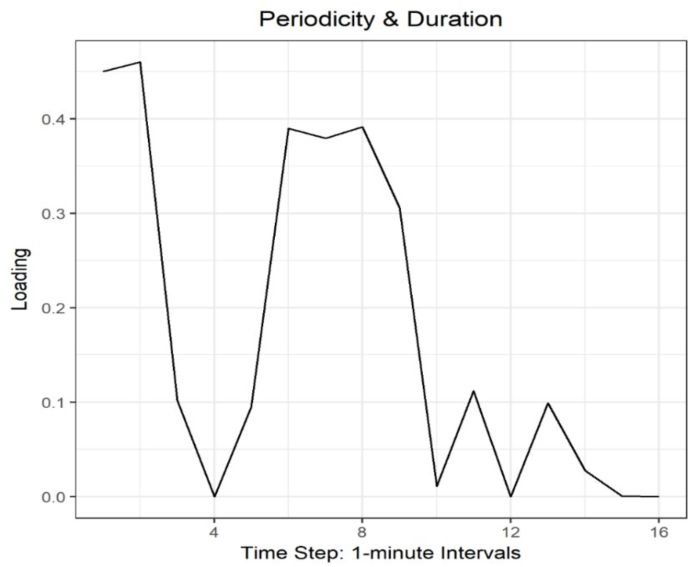


Figure 6: Loadings for Component 1.

Figures 6 & 7 represent tensor component loadings over time for the two most salient components, as extracted from wearable sensor data streams on each individual, as well as their workstations. Over the 16 minutes the team took to complete the entire tower, there were several periods of a particular interaction configuration, exhibited in the two graphs.

For the first component, there are two peak episodes (minutes 0-3 & 6-8). These episodes coincide with our observation of a fairly consistent structure with close interaction between the same subset of participants. Around the 4-minute mark, the group dispersed to work on their own individual tasks, then came together again at the 6-8-minute mark.

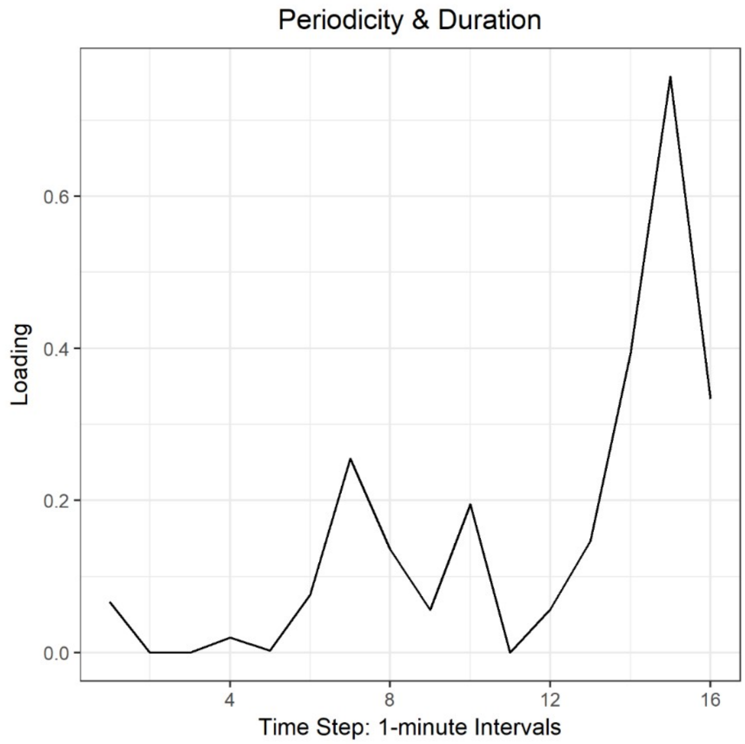


Figure 7: Loadings for Tensor Component 2.

For the second component, Figure 7 depicts a massive spike at roughly the 14-minute mark, with a very high component loading of around 0.7, almost double any of the previous 14 minutes. This spike coincides with the ‘integration’ phase of the collaboration task, when all participants came together to fuse all of their individual pieces into a massive tower.

Tensor decomposition enabled us to detect the duration and periodicity of different states of collaboration and communication. These different states were validated in a review of the corresponding video data. When participants in the non-hierarchical condition began working, they clustered around the instruction sheet, trying to figure out the best way to complete their project. One participant then disassembled the set of instructions leading to participants assembling into self-organized, smaller groups, tackling smaller component pieces. Working off each other's' success, all participants then came together to integrate each individual phase into the larger tower. The integration step, as represented by the loadings on component 2 around minute 14, perfectly portrays the type of collaborative effort a real-life team would undergo to complete an intricate, dynamic project.

Figures 8 and 9 provide a visual representation of the collaborative states captured by tensor components 1 and 2 (Figures 6 and 7). In Figure 8, we see that participants have separated into smaller groups. For example, subjects 7807 and 3456 have formed their own smaller work group on the right side of the figure.

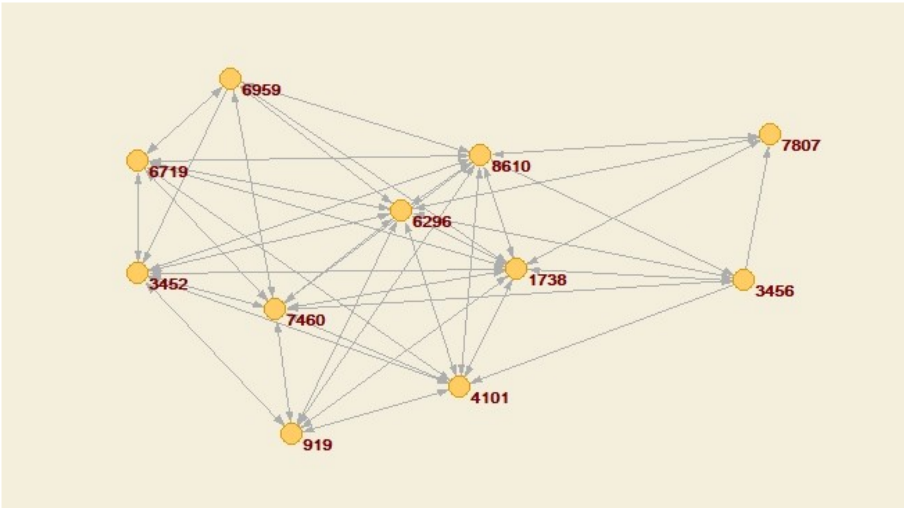


Figure 8: Team colocation network.

In Figure 9, we see an entirely different structural configuration. Participants interact very closely as they have grouped back together for the integration phase of the collaborative task. For example, subjects 7807 and 3456 are no longer working independently of the group.

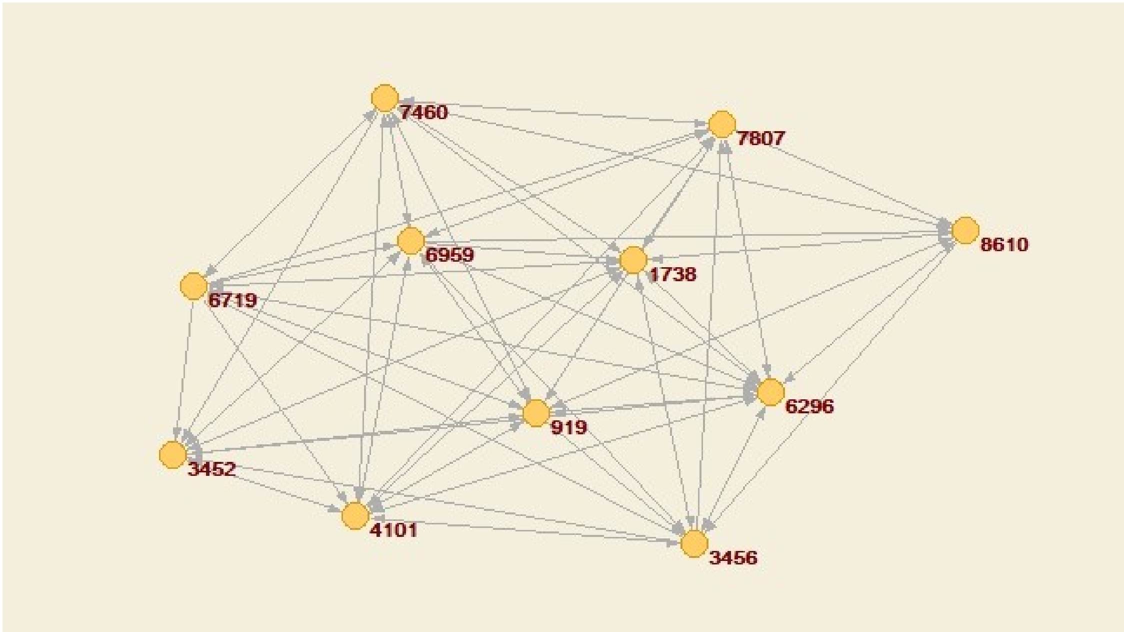


Figure 9: Each individual team member has huddled together to form a more cohesive team structure for the final integration phase.

Our wearable sensor data combined with tensor decomposition methods appears to offer a window into the dynamics of non-hierarchical collaboration and communication. These dynamics expressed in emergent collaborative structures have clear implications for individual and team performance.

It has to be acknowledged that the analysis presented is based on longitudinal data collected for a single instance of a collaborative exercise. Thus, any insights have to be speculative given the limited empirical data. However, the ability to validate our findings based on video data supports the potential benefits of wearable sensors for identifying organizational emergence in the context of non-hierarchical teams.

Importantly, tensor decomposition has been shown to help to visualize otherwise invisible emergent collaborative structures captured by wearable proximity sensors. In contrast, traditional methods relying on average distances between dyads would only project collaboration unfolding as a single, jumbled group, decreasing our ability to properly dissect and analyze these emergent structures (see Figure 10).

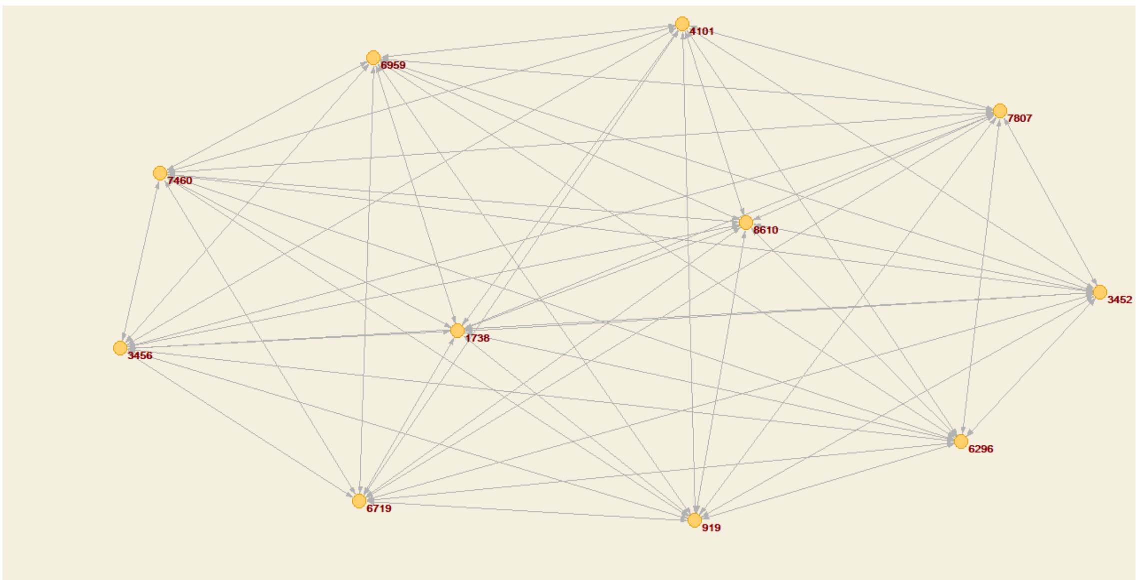


Figure 10: Jumbled networks without tensor decomposition.

Without tensor decomposition, we can visualize each component dyad, but we become agnostic to collaborative dynamics and the emergent structures (i.e., regularities) that are at the heart of many organizational outcomes. Thus, the average network structure shows a rather uniform picture. We see individual sensors moving throughout the network, but no specific points of colocation or inferred collaboration throughout time like the previous networks in Figures 8 and 9. These entangled networks are not very useful because they lack granularity and specificity through time. Because we are working with different dimensions of data, tensor decomposition allows us to see when collaborative states exist and change, for how long they occur, and exactly what they look like. Instead of being blind to these emergent structures and their influence on performance, the current research provides insights into methodological advances that allow us to identify them.

In additional instances of the same experiment, we observed similarly patterned performance and movement under non-hierarchical conditions. This is consistent with the results of my exploratory study and provides further evidence to suggest that emergent collaborative structures in non-hierarchical organizations (1) are dynamic and change over time and (2) can be recognized and analyzed using tensor decomposition analysis on wearable-sensor data.

Chapter 5: Discussion and Future Application

This research set out to explore how wearable sensors could be used to obtain new insights about the complex interplay between organizational design and emergent collaborative structures. A better understanding of the nature of organizational emergence expressed in unplanned, ephemeral collaborative structures holds the promise to facilitate better management practices to improve knowledge transfer and innovative outcomes for individuals, teams, and organizations. My research leveraged state-of-the-art technologies and novel data analytics for an exploratory study.

This effort was motivated by a dramatic shift in the formal organizational design of firms operating in knowledge-based industries. Traditionally, formal structures followed the principles of a bureaucratic organization, which allowed firms to reliably operate at scale, producing consistent outputs. These benefits can be the source of critical competitive advantages in stable environments, but they tend to be achieved at the expense of organizational flexibility. However, in tech enterprises specifically, flexibility has become an increasingly important aspect of organizational performance because technological change has become the norm, rather than the exception in these fast-paced, dynamic business environments. In a data-driven world, the success of innovation-oriented collaborative efforts largely depends on collectives of individuals (i.e. teams) and their ability to adapt, problem-solve, and creatively add value to shareholders. To facilitate greater flexibility, creativity, and collaboration, most R&D operations in technology firms are now based on flat, non-hierarchical structures.

In this research, I contribute to the domain of organizational research methods by exploring a novel combination of data collection and analysis to create a more robust empirical foundation related to the benefits and costs of non-hierarchical organizational design and emergence. Historically, emergent or unplanned collaborative structures have been unidentifiable for organizational researchers and practitioners, making a systematic examination of this phenomena virtually impossible. Consequently, few insights exist about managerial practices leading toward a beneficial contribution in these contexts. In the past, researchers have used surveys, interviews, and self-reporting. While useful, these methods fell short of the mark, only scratching the surface of emergent structures and collaborative dynamics—despite providing a lot of the foundational theory on the topic.

My theoretical model points towards a conceptual gap in our understanding of emergent collaborative structures and their link to performance outcomes. In my empirical study, I attempt to address the methodological gap in identifying them. If we cannot identify, measure, and analyze emergent collaborative structures, then we cannot manage them effectively. But with wearable sensors and tensor decomposition, we can identify and visualize regularities and patterns in the proximity data. More importantly, instead of being blind to the underlying factors of performance, we now have a tangible method of linking emergent collaborative structures to performance outcomes in specific scenarios. Once these links can consistently be made and documented, we can begin to think about how to manage them.

As more and more companies move towards a less-hierarchical model of organizational design, it is imperative to not only expand our understanding of emergent collaborative structures, but also how we can utilize the growing availability of continuous interaction data and wearable sensors to our advantage. It is analogous to a sports manager watching a video-recording of different formations and plays, linking certain movements and dynamics to certain outcomes and overall individual and collective performance. Without seeing these developments, it would be near impossible to decipher which plays—and which scenarios—create the best opportunities for individual and collective success. Thus, my research provides a foundation for developing an original perspective on the connection between emergent collaborative structures, organizational design, and knowledge networks. Additionally, the results represent the first step in identifying those emergent collaborative structures in non-hierarchical organizations using objective data from wearable sensors. With additional research and participants, patterns of self-organization, performance, communication, and other factors would likely emerge that would be incredibly useful for team-based organizations to take advantage of and learn from.[2]

Give the data limitations, I was unable to establish statistical support related to my intuition that non-hierarchical collectives would benefit from increased flexibility, better resource allocation, and overall productivity after initial coordination difficulties. However, my research represents progress in capturing organizational emergence with wearable sensors and visualizing the corresponding collaborative networks. The practical implications of this research are significant, as technological advances in wearables and digital communication technologies will increase the access and ability to analyze continuous relation data. Productivity and efficiency of organizations in every facet of industry from manufacturing to medicine are likely to benefit from a

[2] In a separate study with MBA students, we saw participants break out into self-organized teams by gender. With further research this would be an intriguing pattern to pursue for organizational psychologists.

better understanding of the role of emergent collaborative structures. We have relied quite heavily on the traditional hierarchical model of organization, but this research, along with future research, will open the doors to better and more innovative organizational designs and applications.

Lastly, my research offers a practical contribution to the field of business education. The designed collaborative task offers a unique opportunity to expose undergraduate and graduate business students to the real-world, collaborative challenges organizations in knowledge-based industries face today. While there is no shortage of collaborative exercises used for educational purposes, there are few that model the dynamic, ambiguous, challenging environments that most tech-based firms often live in. As part of my research, I designed, developed, and implemented a collaborative task that doubles as a simple, yet comprehensive team-building opportunity, as well as an introduction to important and advanced organizational design topics using innovative technology.

Conclusion

I start work in January as a supply chain analyst at Intel, one of the most innovative, fast-paced tech companies in the world. Organizational units composed of individuals in different time zones with various skills are still expected to coordinate and collaborate flawlessly, delivering exceptional value to customers and shareholders. Competitors work at breakneck speed to design and manufacture smaller, faster semiconductors, pushing the boundaries of modern physics. Project managers delegate work and resources, individuals break out into smaller groups, and emergent collaborative structures inevitably develop to produce high-quality work. However, as previously discussed, these structures are difficult to identify. In almost every organization in the world, emergent collaborative structures will develop without any control, management, or analysis due to methodological inadequacy. However, my research illustrates the robustness of wearable sensors and tensor decomposition as a valid method of identifying, studying, and potentially managing emergent collaborative structures. Our data-driven world, especially at Intel, will only get more data heavy as we begin to introduce autonomous vehicles, the 5G network, and more connected devices. While this development brings progress, it also represents a significant challenge to ensure we are as efficient, productive, and sustainable with our resources as possible. As I progress through my career, I look forward to facing these challenges, and seeing how my research can inform a practical bridge between organizational design, team dynamics, and emergent collaborative structures to enhance productivity and performance at Intel, and around the world.

Chapter 6: Addendum

Team Instructions:
You have now been divided into a product development team of seven individuals, who each possess different strengths and weaknesses. The overall team goal is to build a three-tiered tower out of differently colored magnetic pieces in the allotted 45 minutes. Each section contains an overview of the tier you are building, a performance goal, instructions that detail how to build each tier, and pictures to guide you. You are free to reference the instruction sheet as many times as you'd like. Good luck.

Tier 1 Overview) Construct the foundation of the tower by building four separate "legs" of the following colors:

- Blue
- Red
- Orange
- Green

Each leg leans in a certain direction. One potential solution is to begin by creating the foundation using two equilateral triangles, so it looks like a rhombus with a diameter, or a skewed square with a piece through the middle. The entire leg should have three "levels". Triangular pieces can then be used to build upwards to a secondary rhombus, and so on to the third one. Each leg should use no more than 40 magnetic pieces and no more than 15 magnetic balls. Only connect magnetic pieces with magnetic balls. Connecting one magnetic piece to another magnetic piece will not be stable enough.

Performance Goal: Build four individual legs that stand on their own and slightly lean in one direction. Each leg should end up having a rhombus at the foundation, middle, and top, that represent three "levels".

1. The rhombus based foundation should use five pieces and four balls, which should end up looking like two equilateral triangles that share the same base.
1.1 Consider the two magnetic balls that are furthest from each other as "points", while the other two magnetic balls are "sides".
1.2 Pick one of the two equilateral triangles and attach one magnetic piece to each of magnetic balls, then connect those three pieces with a magnetic ball so you've built a pyramid over the original equilateral triangle. This is the first "point", of the second level rhombus.
1.3 Then attach two magnetic pieces to the point of the rhombus that has been unused thus far. Each of these pieces should stick upwards and towards the other sides of the foundational rhombus.
1.4 Then attach one magnetic piece to each of the two sides of the rhombus, and connect each of those pieces with the two pieces from step 1.4 using two separate magnetic balls. This should create two new equilateral triangles that extend vertically. Each of the magnetic balls will represent the second and third "sides" of the second level rhombus.
1.5 Connect the three magnetic balls you have now used with magnetic pieces that lay horizontally.
1.6 Attach a third magnetic piece to the point of the foundational rhombus in step 1.4 that juts out at about a 45 degree angle. Add a magnetic ball to the piece,

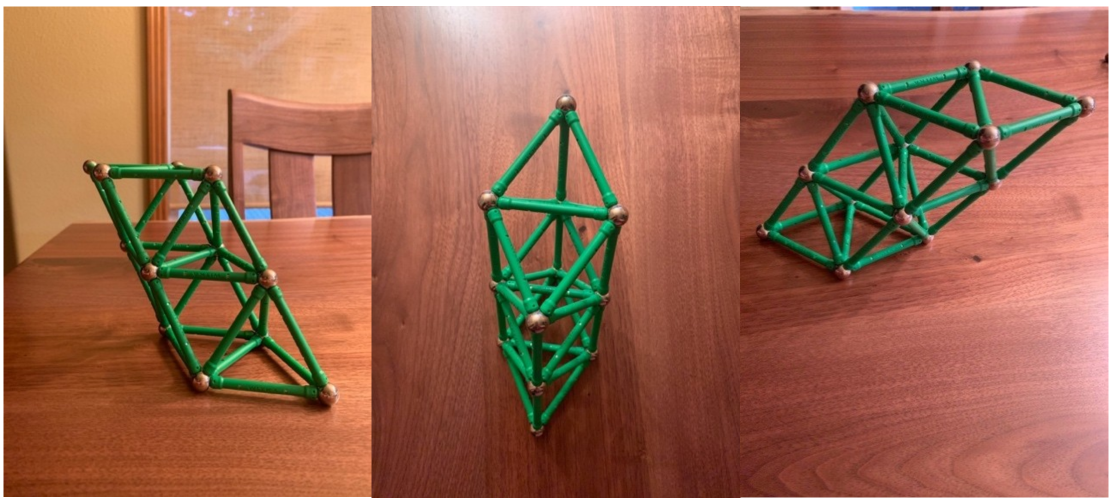
then attach two horizontal magnetic pieces to the other two magnetic balls so you've created the second "level" rhombus.

1.7 Repeat steps 1.1 through 1.7 on top of your original build until you've created four legs with three levels.

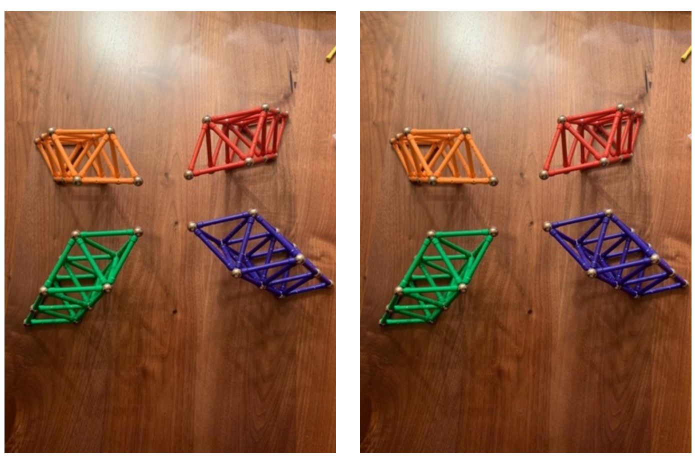
1.8 Once completed, arrange them so you can connect each point (the magnetic ball that juts out due to the leg "leaning") using four magnetic pieces. Once connected, it should look like the legs are connected by a square.

1.9 Then use two additional magnetic pieces to connect one side of each leg with the leg opposite it, to provide more support.

Pictures of how each leg should be constructed are below (remember, each leg should be a different color):



Pictures of how each leg should be connected are below:

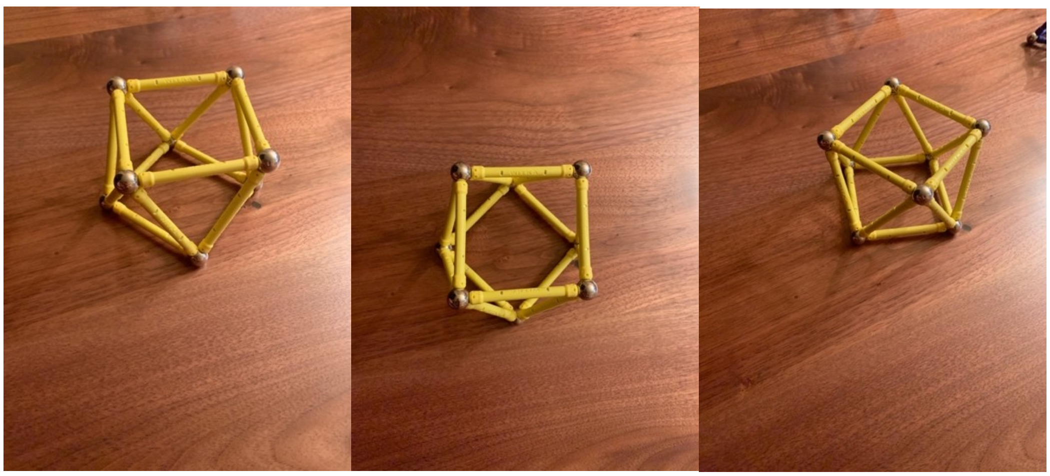


Tier 2 Overview) Build a transition platform that connects the four legs to the tower. This platform should consist of no more than 40 yellow magnetic pieces and 20 magnetic balls.

Performance Goal: Create a modular transition platform that can stand entirely on its own without being connected to the rest of the project.

2.1 Begin with a singular square.
2.2 From each magnetic ball of the square, two pieces should extend upward, creating four triangles that are connected by metal balls.
2.3 From the balls of those four triangles, a new square can be constructed by connecting each magnetic ball with a magnetic piece placed horizontally.

Pictures of how the transition piece should be constructed are below:

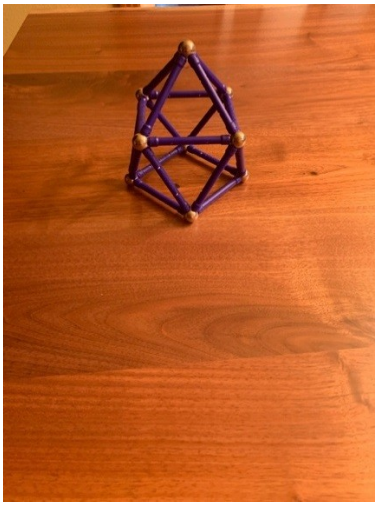
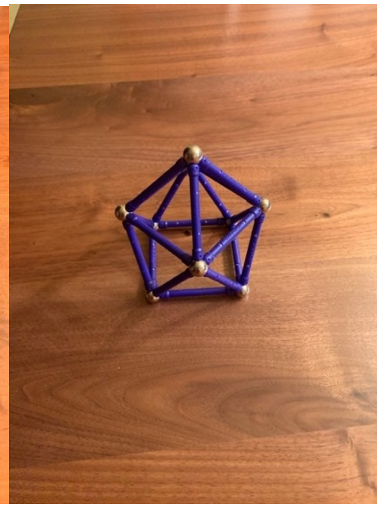
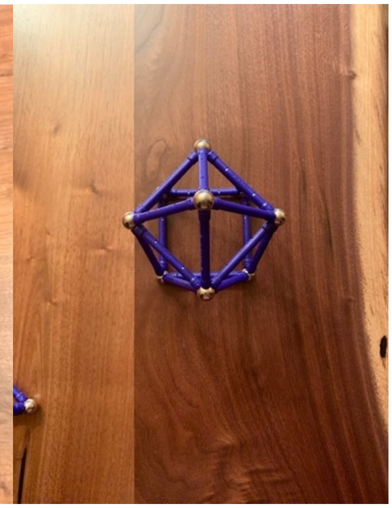


Tier 3 Overview) The final tier is an elongated tower with a pointed top. It's built using a square foundation and triangular support pieces, just like the modular transition piece in tier 2. It should be made out of no more than 40 blue magnetic pieces and 20 magnetic balls.

Performance Goal: A light and stable tower that can easily be placed onto the other modular pieces to complete the entire project.

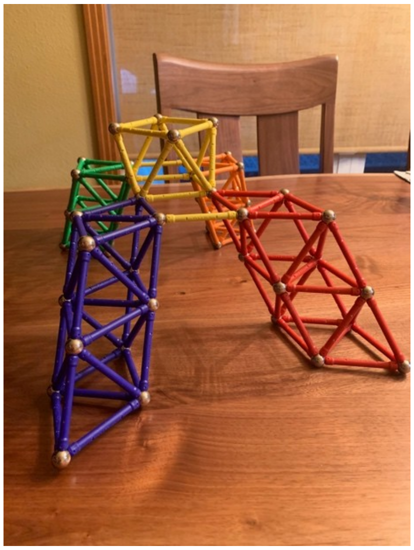
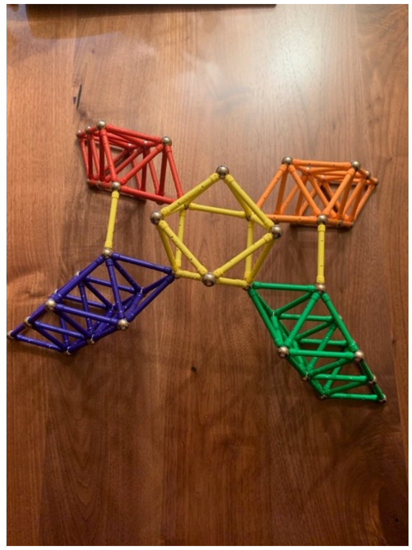
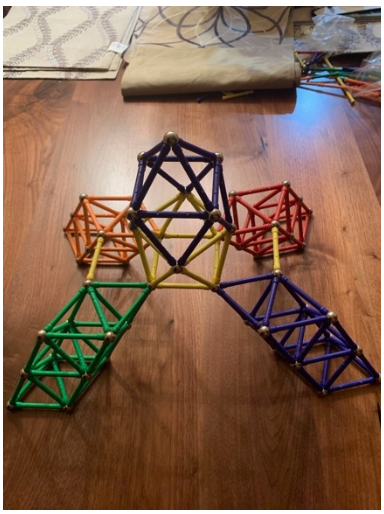
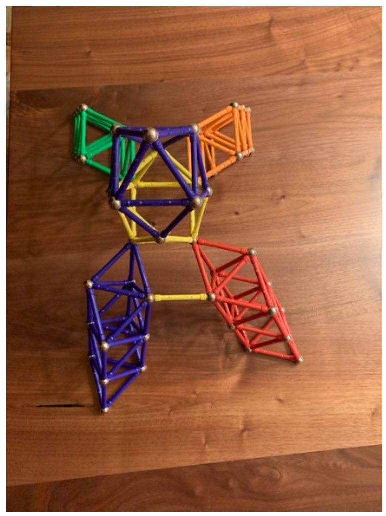
3.1 Begin with a singular square.
3.2 From each magnetic ball of the square, two pieces should extend upward, creating four triangles that are connected by metal balls.
3.3 From the balls of those four triangles, a new square can be constructed by connecting each magnetic ball with a magnetic piece placed horizontally.
3.4 Create the "point" of the tower by attaching a magnetic piece to each of the ends of the square, then connecting those four pieces with a magnetic ball.

Pictures of how the final tower piece should be constructed are below:

Combining Each Part
Tiers 2 and 3 are constructed with a base so they can stand on their own as modular pieces to the entire tower. However, when connecting tier 2 to tier 1, and tier 3 to tier 2, keep in mind that the top of each segment will also be the bottom of the next segment. Thus, you will have to actually remove the bottom of each tier before placing it on the tier below it. For example, the four legs are connected by a square, which will be the bottom of Tier 2 once it's connected. So before placing Tier 2 on Tier 1, you must remove the bottom square so Tier 2's magnetic pieces attach to the magnetic balls of Tier 1. You cannot simply stack one modular piece on to another.

Pictures of how each tier should be connected are below:


Chapter 8: Appendix

Exhibit A: Leg phase

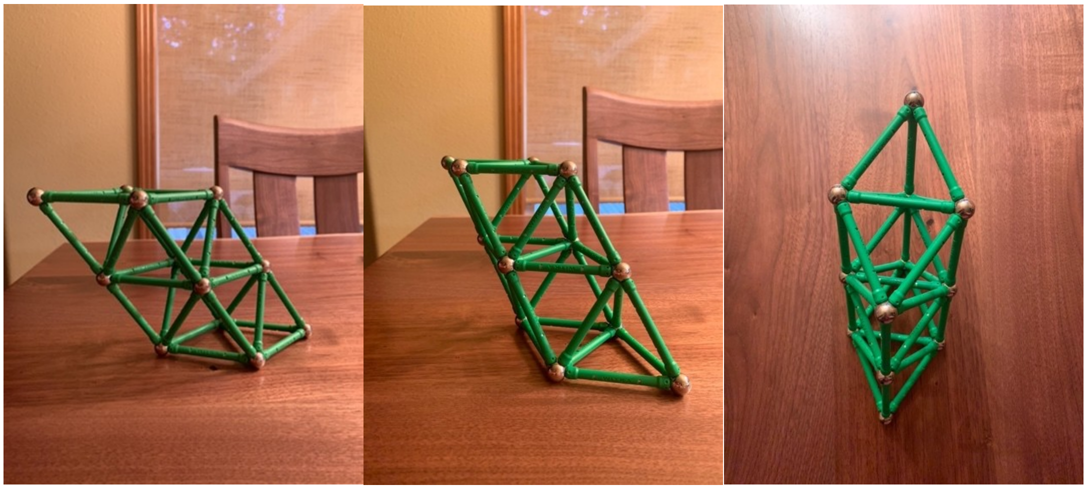


Exhibit B: Middle phase

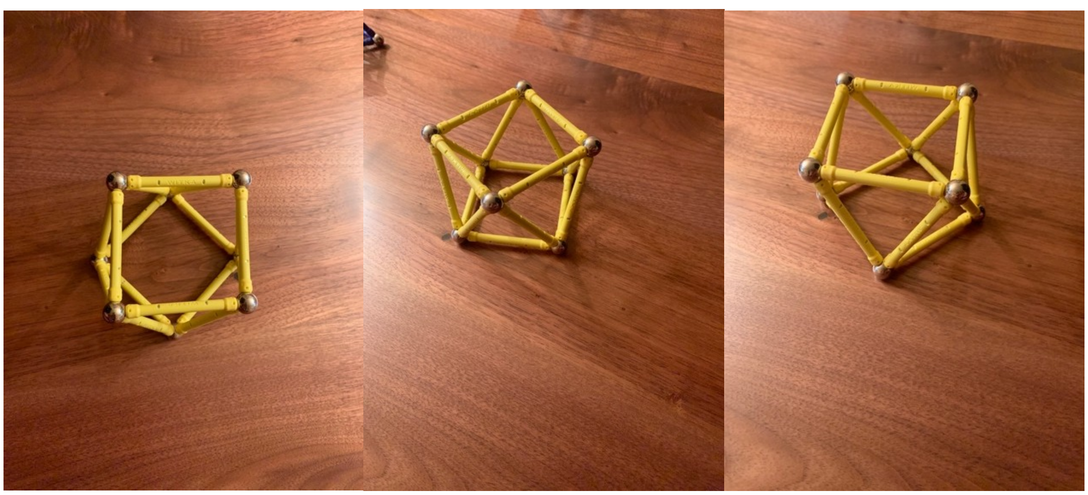


Exhibit C: Tower phase

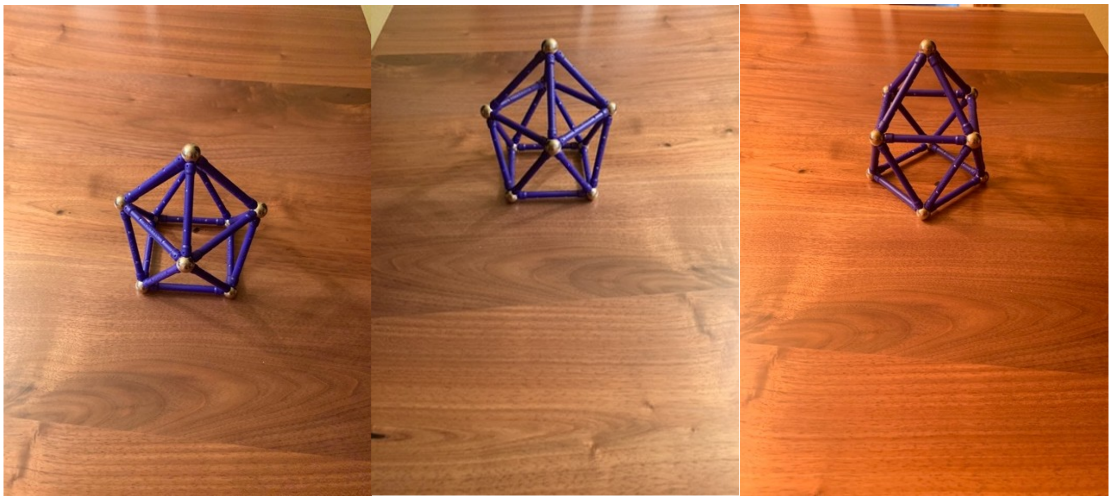
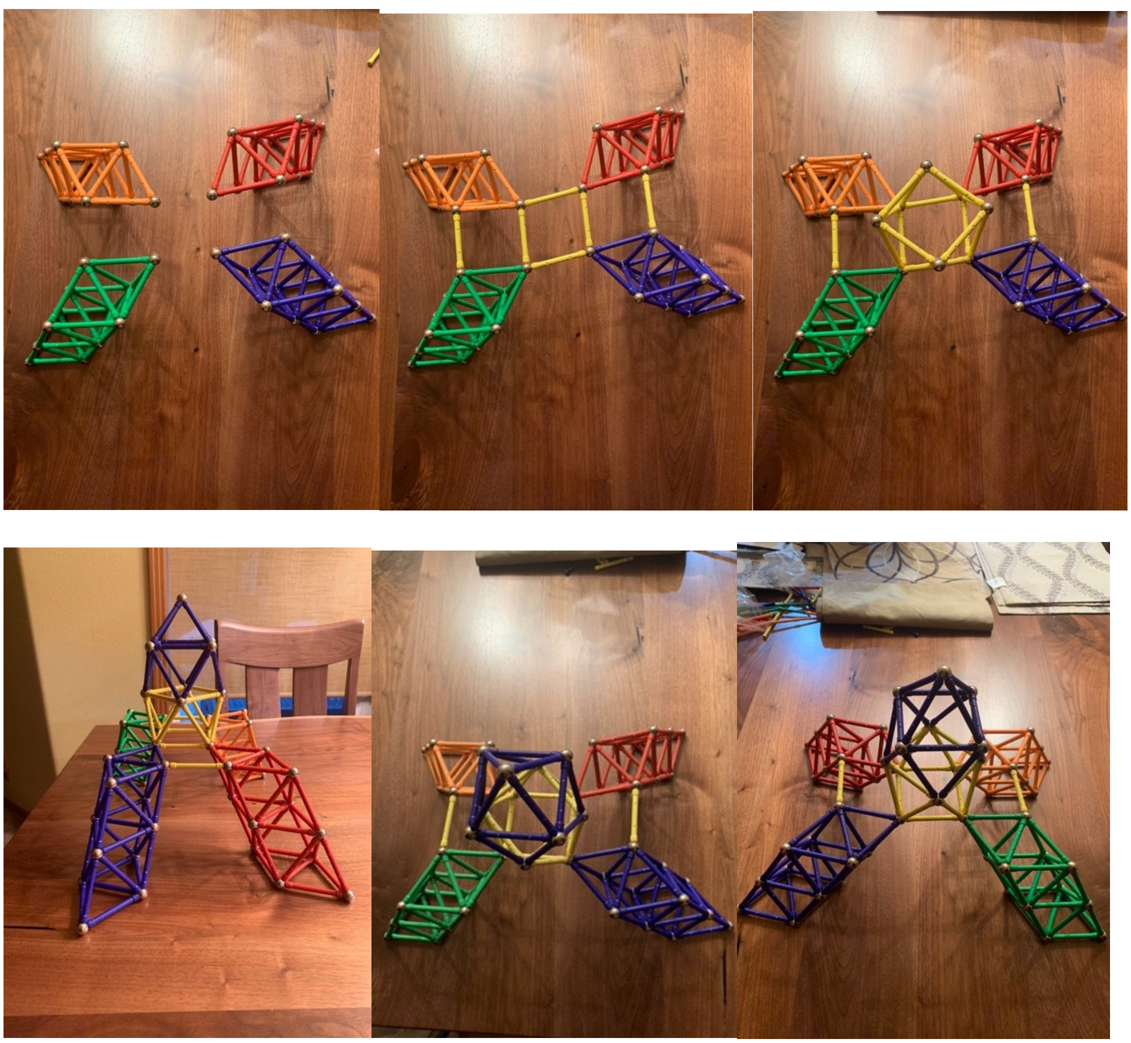


Exhibit D: Integration of all three phases



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