2022

Fractal Dimension as a Predictor of Organizational Change Success

Thomas Anthony Seitz
Walden University

Walden University

College of Management and Human Potential

This is to certify that the doctoral dissertation by

Thomas Anthony Seitz

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Richard Dool, Committee Chairperson, Management Faculty
Dr. Aridaman Jain, Committee Member, Management Faculty
Dr. Keri Heitner, University Reviewer, Management Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2022

Abstract

Fractal Dimension as a Predictor of Organizational Change Success

by

Thomas Anthony Seitz

MA, Walden University, 2020

SM, Massachusetts Institute of Technology, 2003

BS, Michigan State University, 1984

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

August 2022

Abstract

As many as two thirds of organizational change (OC) initiatives fail to achieve their outcome objectives. Researchers have demonstrated that successful change requires alignment among all levels of an organization. However, contemporary OC models do not quantify the degree of hierarchical alignment during the change process. The purpose of this quantitative, correlational study was to examine whether the fractal dimension of hierarchical alignment (predictor variable) was associated with OC success (criterion variable) as described by the self-organizing fractal theory (SOFT). The research question addressed the association between the fractal dimension related to the alignment of OC beliefs and behavioral intentions across an organizational hierarchy and subsequent OC success. The instrument included creolization and change resistance themes to collect primary survey data through the self-selection of 125 North American aerospace workers who had participated in a formal change process. Pearson's product-moment, Spearman rank, and Kendall's tau correlation coefficients revealed a strong positive association between fractal dimension and OC success. Subsequent regression analysis reinforced the positive correlation and explained at least 56% of the observed variation in OC success. The results contributed to scholarly OC research by providing proof-of-concept demonstration that SOFT is applicable to OC research. This study also contributed to social change by creating measures that may lead to improved change management, resulting in less resource waste, lower employee stress, and improved change outcomes.

Fractal Dimension as a Predictor of Organizational Change Success

by

Thomas Anthony Seitz

MA, Walden University, 2020

SM, Massachusetts Institute of Technology, 2003

BS, Michigan State University, 1984

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

May 2022

Acknowledgments

I gratefully acknowledge the support and guidance of my dissertation committee members, Dr. Richard Dool, Dr. Aridaman Jain, and Dr. Keri L. Heitner, who helped me navigate the treacherous waters of my ambitious research project. In particular, thank you to Dr. Dool for your support as my chair and a valued mentor. Your expertise in organizational change was invaluable to my research. Thank you for your guidance and discourse and for acting as a sounding board for my weird ideas about OC mathematics. I cannot express my gratitude for patiently slogging through volumes of my rewrites to help me focus on the meaning while identifying the superfluous content.

I would also like to thank my family for their steadfast support throughout the process. Thanks to my beautiful wife, Kathleen, who patiently endured abject neglect and lost weekends to my studying and research. I am also grateful for the support of my children. Allison, your work ethic inspired me to continue looking for the work's richer meaning. Scott, you inspired me to look at a problem using different perspectives and continue working even when frustrated or overwhelmed. I also thank my father, Richard, for being a role model of support, perseverance, and encouragement to find a pragmatic measure in a seemingly intractable subject. I love you all and thank you for helping me reach this point in my academic career.

Lastly, thank you to the Northrop Grumman Corporation for sponsoring me throughout my academic journey.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

Despite decades of organizational change (OC) research, most change initiatives fail to achieve their objectives (Jones-Schenk, 2019). A 2018 McKinsey report concluded that successful change within organizations is impaired by ineffective prioritization of the change process, a lack of ownership for change, and the inability to measure and track the effectiveness of the change process (Lindsay et al., 2018). Without a measure of success for organizational change, leaders cannot evaluate the progress of the change initiative, which hinders their ability to understand which areas of the organization require help. A meta-analysis by Samba et al. (2021) indicated that measurement strategies drive decision making during the change process and cautioned that more information does not translate into better decisions unless used to assess where to apply management oversight.

As I describe in Chapters 1 and 2, the measurement of OC is challenging, perhaps due to the significant disparity between quantitative OC research and qualitative OC studies. In general, quantitative studies are a small fraction of peer-reviewed scholarly OC literature. In this chapter, I describe my study to examine whether fractal patterns of beliefs and behaviors across an organizational hierarchy are associated with organizational change success. The results from this study may help narrow the gap in contemporary social research by providing a physics-based look at OC measurement using fractal mathematics. Later in this chapter, I describe the problem with conventional OC studies and discuss why self-replicating fractals are capable of expressing organizational change. I also provide supporting evidence for the possibility of a practical measure of organizational alignment using fractals to describe organizational behavior across hierarchies. I introduce my research question and describe my study and the planned sources for my data collection. I also present the self-organizing fractal theory within a fractal emergence framework and provide an objective review of the limitations and boundaries of my study. Although I did not test for causality between fractal measures and change success, I describe how I planned to discern whether fractal dimensionality and OC success were correlated. A positive correlation between OC success and fractal dimension (FD) may open the door for additional studies exploring fractal emergence as a real-time measure of change.

Background

Although the field of organizational change is well researched, there is very little multimethod validation that quantifies how individual actions relate to cumulative OC success (Harms & Credé, 2010). Despite more than 3 decades of formal OC research, preengineered change initiatives rarely succeed (Bolman & Deal, 2017; Dorling, 2017; D. King & Land, 2018). Part of the predicament lies with change research. Contemporary organizational change research tends to describe OC through qualitative paradigms and metaphors. Sorge and van Witteloostuijn (2004) criticized the erudite use of qualitative metaphors to describe an OC process, claiming that broad visions of transformation fail to capture the physics of change at the detail level. Sorge and van Witteloostuijn advocated for an evidence-based quantitative method to associate specific actions with their impact on the organization.

Hoff and Scott (2017) indicated that organizational change is associated with social learning and individual worker agency. Hoff and Scott described how learning leads to workforce decision-making changes and how the accumulation of individual decisions and actions leads to overall OC. Although Hoff and Scott did not quantify the relationship between alignment and outcome, it is reasonable to suggest that a quantitative appraisal of individual beliefs and behaviors across an organization could lead to a measure of OC. However, quantifying individual actions during OC is difficult, except when done in the most general terms (Axelrod & Axelrod, 2017; Hallencreutz & Turner, 2011). For OC research to advance, it must address the relationship between alignment and success. For example, Jevtić et al. (2018) argued that the key to understanding change is to measure alignment between hierarchical levels across the organization.

Organizational Change as Self-Replicating Fractals

An organization is not a static entity with a single, uniform will and purpose; rather, it is a collection of individuals who make decisions at an elemental level that integrate and impact organizational inertia. Nielsen and Lund (2018) characterized successful change management as an organization’s ability to translate inputs into outputs that scale from the lowest level of the organization through the executive ranks. When individual and collective decisions become habitual, and those habits align with tactical or strategic objectives, the desired behavior results in change (Jayatilleke & Lai, 2018). Because OC is a form of expected behavior, replicating change behaviors must emerge throughout all levels of the organization before an organization can overcome its inertia and change.

Schirmer and Geithner (2018) proposed that individual workers collaborate by resolving contradictions and establishing new social norms. When social norms are practiced across the organizational hierarchy, a dynamic learning community creates a shared vision of the change process (Caulfield et al., 2021). A shared purpose and culture provide a common context for individual decision making that scales throughout the organization. Therefore, it should be possible to express and measure organizational change in terms of self-replicating (fractal) behavior across a company's hierarchy.

Aligned Hierarchical Behaviors Result in Quantifiable Fractal Patterns

In the late 1970s, Prochaska (as cited in Biehl et al., 2018) observed that people do not progress linearly through a change process; rather, they alternate between positive and negative choices and actions. Individual behaviors contribute either positively (toward the objective) or negatively (away from the objective). When the workforce's beliefs, actions, and behaviors align, its desired performance sustains and promulgates change (Brantley, 2009). However, the actions of workers and leaders may not align, and contemporary OC research indicates that this misalignment between functional levels within a firm can lead to unsuccessful change (Lazzarini, 2020). I propose that measurable fractal patterns must emerge in the form of self-replication through all levels of the organization for a change to be successful.

Fractal decisions accumulate to resolve into a transformative force that overcomes organizational inertia. The decision process must be repeated and promulgated throughout the organization for individual choices and behaviors to collect into a net-positive outcome. Hussain et al. (2018) studied organizational change success and found that workers behaved like fractals within a complex adaptive system during successful transitions. Hussain et al. showed that individual change actions succeeded when workers across the organization shared a prevalent view of the benefits of changed behavior commensurate with the organizational goals for change. Hussain et al. supported the concept of fractal-level interaction between decision makers by demonstrating the effectiveness of communication between employee–employee, employee–leader, and leader–leader dyads toward regulating change efficacy. However, Hussain et al. failed to apply fractal mathematics to their study and describe fractals beyond their metaphorical use.

A knowledge gap existed in organizational change research regarding the quantitative link between fractals and change. Although many social researchers had speculated that corporate operations are expressions of fractal behavior, few had attempted to quantify the nature of hierarchical alignment, and none had quantitatively linked fractal properties to OC success (see Malik, 2015; Nonaka et al., 2014). However, as individual actions align throughout the organization, the change process creates a self-reinforcing loop that bolsters belief in its leadership (Borgogni et al., 2011) and perpetuates positive OC. Assessing the degree of self-replication within and between hierarchical levels in a changing organization may lead to a means by which to measure and predict OC success.

Berberoglugil and Şatir (2012) proposed that fractal patterns naturally occur in organizations and could be used to overcome the inability of traditional research methods to measure complex systems. Berberoglugil and Şatir suggested that a fractal view of change could overcome the inherent issues with monolithic OC studies. However, although some scholars have concluded that OC requires self-replicating behavior across the organization, researchers had not quantified the relationship between behavioral alignment and OC success.

Despite decades of OC research, most change efforts fail to achieve their objectives. There is scholarly evidence to support the notion that fractal properties are present during successful change. However, researchers had not used fractal mathematics to measure organizational alignment during OC. The goal of my research was to examine whether fractal dimensionality correlated with OC success. Results may provide a proof of concept that quantitative fractal theory applies to social research beyond its symbolic use.

Problem Statement

There is a general lack of practical quantitative models to assess success in OC, especially as they apply to large, complex organizations (Croitoru et al., 2018). Without the means to measure change, successfully managing the change process is challenging, and OC failure is abundant. As many as two thirds of formal OC initiatives fail to achieve their desired outcomes (S. King et al., 2018). Extant social research has shown that successful change requires attitudinal and behavioral alignment between workers and leaders at all organizational levels (Miake-Lye et al., 2020; Stame, 2010). However, measuring the degree of alignment between and within hierarchical levels during the change process is difficult because organizational systems are complex, and individuals within the organizations do not perform uniformly or simultaneously during the execution of change initiatives (Pianesi, 2019).

The specific problem in extant change research is that it fails to provide a quantitative link between organizational alignment and OC success. Without an adequate alignment measure tied to success, leaders cannot know where to redirect change management efforts, which lowers the effectiveness of the change process. Organizations have little ability to alter their management practices during the change.

Pryor and Bright (2014) characterized organizational management systems as chaotic strange attractors and suggested that fractal patterns within the system were the key to simplifying their quantification. However, quantitative fractal research has not been applied widely to OC. I investigated OC as an aggregation of fractal patterns across the transforming organization using FD measures. I conducted a study to evaluate FD as a quantitative predictor of OC success. The availability of an OC predictive tool might enable leaders in North American aerospace companies and other industries to measure and manage OC more effectively. A practical measure of alignment to change goals may reduce the projected $2 trillion (worldwide) wasted annually on failed program strategy implementation (Business Wire, 2018).

Purpose of the Study

This purpose of this quantitative study was to examine whether measurable fractal patterns of expressed beliefs and behaviors across an organizational hierarchy were positively associated with OC success. I evaluated whether the FD predictor variable correlated with the criterion variable of OC success. The use of fractals to quantify the alignment of beliefs and behavioral intent may result in a quantitative fractal emergence model capable of providing a practical measure of OC. However, I limited the scope of this effort to a proof-of-concept test for the correlation of fractal patterns across organizational hierarchies with the degree of success for a given change initiative.

Research Question and Hypotheses

I conducted a quantitative study using a survey instrument to measure the degree of self-replication within organizational hierarchies based on the internal consistency of responses regarding organizational creolization and resistance to change. For this proof-of-concept study, I surveyed employees within North American aerospace companies who had recently completed or were completing an organizational change. My research question was created to determine whether I could measure and predict organizational success using a FD based on the degree of self-replication across hierarchical boundaries. My approach was similar to the method used by Hassan et al. (2013) to model the self-replication of stochastic Brownian particles undergoing consolidation. However, in my study I considered replication across organizational hierarchy levels instead of replication across quantum energy levels. I questioned whether there was a correlation between the calculated FD based on the alignment of OC beliefs and behavioral intentions across an organizational hierarchy and the expressed OC success of that change:

RQ: Is there an association between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success?

H_0: There is no correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

H_a: There is a statistically significant correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

Theoretical Framework

Contemporary scholarly research supported the notion that successful organizational change is possible, despite the low percentage of success (Sune & Gibb, 2015). I hypothesized that if successful OC is possible, it should be measurable through quantitative means. My research was guided by the self-organizing fractal theory (SOFT), which characterizes stochastic systems through scale-invariant, self-organizing fractal equations. I used survey data to quantify the degree of self-replication of an individual's perceptions of how their personal beliefs and behaviors relating to the change compared to those of their colleagues, workers, managers, and executives. The survey included several questions regarding the participant's perception of the OC success outcomes. SOFT was appropriate for this quantitative inquiry because it served as a way to mathematically characterize self-scaling and self-replicating behaviors and beliefs throughout a complex organizational network. I used SOFT for its ability to describe how networks of individual actions and decisions within a complex system can be pragmatically modeled without the need to explain the motivations behind the actions (see Kurakin, 2011; Zimmermann, 2018).

Nature of the Study

I selected quantitative methodology because my research question referred to an association between OC success and the FD. I used a descriptive, nonexperimental correlative design. A quantitative approach was appropriate for my research purpose because I sought to test the statistical strength of the association between fractal self-replication and perceived OC success. Burkholder et al. (2016) advocated for the use of correlational designs when the experimental variables can be measured but cannot be manipulated to infer causality. As indicated by my research question, I evaluated two variables for a relational association. Correlation studies are bidirectional, meaning that the outcome cannot conclude that an association between the independent predictor and dependent criterion variable is causal (Burkholder et al., 2016). Therefore, both independent and dependent variables lose their cause-and-effect meaning in correlational studies and are commonly referred to as predictor and criterion variables. Because OC efforts are expected to cause change through employee actions, and because the change outcome is realized after the OC action, there is a temporal link between action and success. OC actions precede attributions of success. My research question addressed whether the hierarchical alignment of actions could be expressed using a FD. Given that hierarchical alignment begets successful change, I reasoned that there should be a temporal connection between the FD relating to hierarchical alignment and OC outcome success. Based on a precursor–successor relationship, the FD was the independent predictor, and the participant's description of OC success was the dependent criterion variable.

According to Edmonds and Kennedy (2017), the two most common approaches for nonexperimental designs are observational and survey approaches. An observational approach was impractical for my research because of my lack of access to individuals within the aerospace community for observation. Conducting a live experimental study within an aerospace community would have been arduous due to security and proprietary concerns (see McCrie, 2016). However, Edmonds and Kennedy characterized survey research as an efficient and effective method to understand the individual, team, and organizational characteristics within a social research setting. Therefore, I selected a survey approach to answer my research question.

The advantage of a survey approach was that it did not require direct control of the independent variable, nor did it require the measure to be made concurrent with the OC process. The survey method allowed me to assess the independent predictor variable and the dependent criterion variable concurrently or retrospectively (see Edmonds & Kennedy, 2017). I sent my survey to North American aerospace workers who completed or were completing a formal OC process within their organization. Because my survey approach gave me no capability to simultaneously manipulate the predictor or criterion variables, my study was retrospective. I asked participants to reflect on elements of alignment and their perceptions of success, which suited a retrospective survey method as part of a nonexperimental, correlative design.

My research involved a fusion of two validated surveys that had been used to study factors relating to OC beliefs, actions, and success. I adapted a survey by Ai et al. (2019) to measure the degree of creolization present during a change. The Ai et al.

instrument measured how beliefs across an organization changed during OC. Ai et al. demonstrated that cultural change was associated with identity multiplicity, cultural hybridity, boundary spanning, and network expansion. I also employed a survey tool developed by Li et al. (2016) to assess cognitive inertia and resistance to change. Li et al. developed their survey to determine how employees resisted knowledge management systems. Li et al. demonstrated that cognitive inertia and resistance to change related to individual actions and beliefs that shaped the quality of the OC change process. The two surveys, in concert, allowed me to assess how individual and organizational thoughts and behavioral intents align as part of the change process.

Deloitte (2016) reported that approximately half of the North American aerospace companies had recently undergone a significant organizational change. Therefore, a self-selected set of responses from North American aerospace workers was appropriate for collecting relevant data relating to OC self-replication and respondents' perceptions of the resulting OC outcome success. My study was limited in scope to provide anecdotal proof-of-concept testing to determine whether FD for hierarchical change alignment and OC success were associated. I deployed the survey to volunteer members of North American aerospace organizations. I also solicited volunteers ($N > 113$) from the social media sites LinkedIn, Facebook, SurveyCircle, and the Walden participant pool. Because my survey instrument was a fusion of two previously validated OC surveys, I did not revalidate the instrument prior to its use. However, I checked the internal consistency of the two surveys to ensure that my results were consistent with the original authors using post hoc analysis and structural equation modeling similar to how software models are validated using independent data sources (see Marinescu et al., 2015).

I conceptualized the FD as the degree of response alignment between individuals from the lowest levels of an organization to its highest level. Based on survey responses, I calculated a FD for each respondent based on their perception of how their individual beliefs and behavioral intent compared to others across their organizational hierarchy during the change process. I then determined whether there was a valid statistical association at a 95% confidence level between the calculated FD and the respondent's perception of success for that specific change initiative.

Definitions

I used concepts that had specific meanings relative to the study and within a novel framework for OC. Because many of the terms used in my study were borrowed from adjacent fields of math, physics, and management studies, the following definitions are provided to clarify their use in this study:

Creolization: The process by which cultural change is adopted by other cultures through attitudes and behavioral alignment (Webster, 2016).

Fractals: A mathematical description of geometric patterns that are governed by a single set of mathematical algorithms and are recursive and self-replicating throughout a structure. Vakili (2018) described fractal systems as nonlinear complex systems that become self-organizing based on replicating behavioral patterns that emerge due to the interdependencies between the actors within a system. Complex behavioral topographies can be described by fractals through their self-replication at the smallest unit of their elemental shape to the largest scale within their scope (Han et al. 2021; Mandelbrot, 1982).

Fractal emergence: The concept that OC emerges as the cumulative result of individual, self-replicating behaviors and actions (fractals) that scale throughout an organization to provide a collective force that acts to influence organizational inertia (Fryer & Ruis, 2004).

Fractal self-replication: The degree to which self-similar behavior aligns within a hierarchical level and is duplicated across hierarchical boundaries with respect to a common change objective. Organizations with high degrees of fractal self-replication are expected to have self-similar patterns of alignment to a goal despite having different work products; each contributes to the common objective according to their role (Esch, 2004).

Organizational change (OC): A planned set of activities designed to change a company's operational inertia (Hopkins et al., 2013) to improve performance or job satisfaction through modification of the organization's beliefs and functions. OC empowers new ways of working, typically through employee innovation and improved decision making.

Self-similar alignment: The degree to which individual beliefs or actions associated with a desired behavior or outcome associated with a change initiative are present within a hierarchical level or the working group within a social network regarding a common change objective (Mentore, 2012). Groups with high levels of self-similar alignment may perform different tasks but share a common (collective) goal and work toward the desired outcome. Self-similar alignment with a hierarchical level begets fractal self-replication across hierarchical boundaries and is an antecedent to fractal emergence.

Stochastic systems: A complex grouping of objects or actions that appears to exhibit random behavior that cannot be predicted but can be analyzed statistically using random distribution approximations (Merriam-Webster, n.d.).

Assumptions

This quantitative study included several assumptions tied to my methodological choices. According to Creswell and Creswell (2017), a fundamental premise of quantitative inquiry is to characterize or predict observable reality. I used a survey instrument to provide the data I needed for my study. Therefore, I did not directly observe reality and relied on the participants to respond free from bias and uncertainty. Implicit in the use of a survey is the ontological assumption of respondent objectivity. In their study of respondent objectivity in survey use, Kovač and Cameron (2021) observed that most survey participants attempt to be objective, but some may not have the same contextual understanding of the definitions of terms used in the survey. Kovač and Cameron cautioned that survey language must be tuned to the audience and tailored to the participants' level of understanding of the survey's taxonomy and semantics. The surveys I adapted for this study were designed to be used in an information technologies (IT) environment spanning several continents. Both surveys were validated for a broad audience and included relatively simple questions. However, the taxonomy and semantics used for IT organizations were slightly different from those used for aerospace organizations. I had to rephrase the survey questions to address the contextual aspects of the aerospace industry. I believe my rewording of the survey phrasing did not impact the questions' intent or their meaning regarding OC; however, I made the axiological assumption that my paraphrasing was free of bias. I also made the rhetorical assumption that my wording provided the nonemotive directions and the context necessary to engage the study participants.

To frame an executable study, I was required to make some assumptions regarding scope, extent, and data quality (see Helmich et al., 2015). The assumptions I made when deploying my experimental methodology were necessary for a timely and cost-effective study. I used a retrospective survey because I did not have access to individuals within each aerospace organization, and the organizations would not have been likely to allow me to design a controlled OC experiment using their staff. Even if I had been able to design and create an OC experiment and fund its execution, the effort would likely have spanned years. Fischer (2016) estimated that North American aerospace organizations' typical large-scale OC time frame occurs over a 3-to-10-year time span. A retrospective survey design is not without assumptive challenges; however, it was the best design for my time frame and research goals. Because my research question was correlative, a survey design using Likert-type scales fit well within Burkholder et al.'s (2016) criteria for a question-led research approach. Moreover, my use of validated surveys and numeric participant response scales provided sufficient power and precision to answer my research question.

Scope and Delimitations

My use of fractals to simplify complex and seemingly unmeasurable behavior aligned well with the principles of fractal mathematics used in chaos theory. This study may reduce the knowledge gap related to using physics-based tools in management studies. However, my investigation was designed to be a proof of concept only; I did not assess the entirety of chaos theory or other physics-based principles relative to OC success. Nonetheless, my study may help quantitatively describe the qualitative premises from other scholarly researchers who had postulated that successful change should appear as self-replicating fractals (see Berberoglugil & Şatir, 2012; Hussain et al., 2018; Pryor & Bright, 2014). In a small way, like other quantitative OC research, my study may help address the imbalance between quantitative and qualitative tools used to assess OC success. My inquiry may help expand the body of knowledge of social research by applying fractal mathematics to hierarchical alignment during OC. Prior to this study, a quantitative fractal measure of hierarchical alignment was hypothesized but had not been demonstrated. I connected a physics-based view of change to the body of knowledge describing the critical factors influencing successful OC.

I selected my study design to address many of the research problems described in the research problems section. My nonexperimental correlative research was successful in evaluating the association between fractal dimensionality and OC success. Although my study did not necessarily result in a real-time measure of change, it paves the way for other researchers to build on my results. Proof of a valid statistical link between organizational alignment and OC success may lead to studies that allow for real-time alignment measures. A practical OC real-time measure may provide corporate leaders with the information they need to adjust their management practices before time and money are wasted on failed change projects. My results may provide evidence that organizations operate within a self-organizing fractal paradigm. In that regard, my study appears to be the first of its kind in OC research.

Populations Included and Excluded in the Research

My research goals were ambitious and relied on the ability to discern patterns of self-replication and OC outcomes. Although SOFT conceptually applies to all complex systems, I could not test for all organizations and geographic locations. Therefore, I chose to limit my survey to the North American aerospace community. This choice excluded nonaerospace workers and aerospace workers not located in North America. I recruited study participants using self-selection sampling. Self-selection sampling is a nonprobability sampling technique that limits the generalizability of a study's findings to a narrow demographic. To ensure as broad a candidate pool as possible, I used social media sites Facebook, LinkedIn, Walden participant pool, and SurveyCircle to solicit participants. A self-selection sample of social media sites introduced researcher bias because it did not allow me to learn about aerospace workers who were not affiliated with these social media sites. Selection bias posed a distinct threat to the internal validity of my work. I mitigated some of the risks of selection bias inherent in nonrepresentative self-sampling by including a statistically significant sample size. I further lowered selection bias risk by reviewing the participants' demographic information and screening responses to ensure adequate representation for my selected demographic groups.

Theoretical Frameworks Most Related to the Area of Study That Were Not Investigated

I chose SOFT as the theoretical framework to guide my investigation. SOFT was appropriate for my study because it describes the nature of fractal dimensionality and self-replicating behavior in complex systems. However, there are other theories that I could have selected to answer my research question. Because the use of a theoretical framework can influence a researcher's method of inquiry, I considered how my choice of method impacted the internal validity of my work. SOFT views complexity through the lens of self-organization and scale replication. I considered and excluded alternatives to SOFT, including actor-network theory (ANT) and complexity theory (CT).

Michael (2017) described ANT as a theoretical view that begets a methodological approach to social theory based on the idea that individuals are connected through social networks that are constantly shifting and ephemeral by nature. Abdallah et al. (2020) proposed that the ANT helps reveal the complex dynamics that arise during the operation of a business by identifying key actors (human and nonhuman) and defining the possible associations between them. Abdallah et al. found that a network analysis helps researchers understand the interaction between actors and objects. Abdallah et al. also claimed that ANT allows the researcher to visualize how actors' roles will shift over time until repeated behavior results in a new status quo. Although ANT describes social network interactions, the theory does not provide a specific quantification of change. The network maps created during ANT are contextually relevant only within the organization or group. Although SOFT paradigms are not necessarily at odds with ANT, the former theory provided a quantitative methodology that directly addressed my research question. Therefore, ANT was excluded from further consideration.

The second alternative conceptual framework that I considered was CT. CT accounts for interactions between actors in a social network based on unpredictable feedback loops constrained by their applicability rules (Manson, 2001). Heileman et al. (2017) proposed a relatively simple metric that could be used to measure the resulting complexity of an actor feedback loop, and Reeping et al. (2021) demonstrated that complex organizational behavior could be simplified using network diagrams measured by Heileman et al.'s metric. Reeping et al. ascertained that increases in complexity were associated with lower change effectiveness in the short term; however, Reeping et al. stipulated that the Heileman et al. metric would not apply as change became institutionalized. As a theoretical framework, CT shares some of the same benefits as SOFT. CT applies to all levels of an organizational system and uses a mathematical framework based on entropic principles to measure interactions between actors within the system. The use of CT allows for the quantification of complexity during the change process, which would have enabled me to assess the association between complexity and OC success. However, CT has some limitations compared to SOFT. CT requires specific knowledge of the entropic state of the system being measured. A researcher employing CT must have extensive knowledge of the organizational structure as well as the experience and skill to map the feedback loops accurately to derive a complexity value. Therefore, I selected SOFT in favor of CT for my theoretical framework because SOFT did not require special knowledge of the organizational system and had broader applicability to social systems of all sizes.

Methodologically, my research question, which was shaped by the SOFT theoretical framework, led me to use a survey instrument to measure alignment and change. Phillips (2017) reported that over half of all quantitative studies include surveys as the research instrument. Surveys have many benefits, including low costs, relatively rapid responses, and the perception that they are simple to use (Phillips, 2017). However, surveys also have limitations due to the limited number of people willing to participate in them. It can be challenging to elicit responses from a uniform cross section of the target population. Furthermore, data analysis results can become occluded by biases resulting from nonresponses, recall bias, and improper interpretation of questions or responses (Downing, 2004; Fink, 2015).

Despite the popularity of surveys, there are other quantitative methods to consider. For example, Henrique et al. (2019) used machine learning algorithms to evaluate objective reality by creating a meta-analysis of contemporary scholarly literature to harvest data from text as an alternative to surveys. Henrique et al.'s research method showed promise as a means by which to collect heuristic data; however, it was novel within the context of OC research. Henrique et al. described similar heuristic data-mining methods that could be used in place of surveys, such as complier averaged causal effect, bifactor item response theory (IRT), mixture item response theory, and multiple-group categorical confirmatory factor analysis. According to Henrique et al., these techniques require little human involvement and provide an unbiased interpretation of results with fewer ethics complications than survey research. However, the use of heuristic data techniques as a replacement for surveys implies readily available data, which obviated their use in my study.

Generalizability of the Results

I anticipate that the results from this study could lead to a novel conceptual framework for OC. Although there are many ramifications for fractal emergence measures based on self-organizing fractal theory, they could not be tested within the parameters of my study. I restricted the scope of this study to examine whether there was an association between FD and OC success. Dimensionality is one way to assess the fractal properties of a dynamic system. A more complex analysis could have included dynamic effects such as entropy and dissipation rates, similar to the way Mitić et al. (2020) assessed fractal thermodynamics in ceramic sintering. A simple dimension sufficed for my research question, but it did not provide the generalizability to the full extent and breadth of SOFT. Therefore, my results are generalizable as a proof of concept for fractal measures as a reasonable means to quantify and measure change.

Limitations

Marczyk et al. (2005) described internal validity in a correlative design as the ability to associate predictor and criterion variables while ensuring that implausible alternative explanations are rejected. Marczyk et al. advised researchers to attempt to randomize participant demographics as much as possible and add demographic metadata to the survey to allow for analysis and possible statistical controls for demographic variables that make the populations different. A limitation of my study was that I used a purposeful sample of voluntary participants based on their self-selected attribution that they worked in a North American aerospace organization. As such, I did not have a truly random sample stratified across representative demographics.

Another limitation of my study was that it was a retrospective evaluation. I selected a retrospective design because it allowed me to answer the research question without the need to design an experiment. However, because the retrospective study was restricted to correlation analysis, I could not provide a causal model for OC success, nor was I able to measure OC success in real time. Additional experimental studies are needed to refine fractal OC predictive measures. However, this study should help demonstrate that further SOFT-based studies are warranted in social research.

My methodological approach treated individual responses as a blind sample. Although a blind sample is mostly free from selection bias, this approach could have introduced sponsor bias because the participants were selected through their affiliation with a social media platform. If the participant had strong opinions about their organization or profession, their responses could have introduced a bias based on those strong emotions or opinions. To circumvent or minimize this potential bias, I carefully worded the survey questions using neutral statements with objective measures of agreement.

Another limitation of the research was that I used a relatively long survey. The survey instrument contained 34 questions, four success measures, and 10 demographic questions. There was a risk that some participants might lose interest in the study or that their attention would be dissipated over time. I included multiple questions for each of the creolization and resistive intent subcategories to address this risk. Although similar questions helped me assess variation in the participants' responses, they also introduced the possibility of habituation bias, whereby similar questions are answered the same way without much thought regarding the answer. To mitigate this risk, I used a random order of the questions, which helped distribute the uncertainty in response attentiveness over the entire question population. Question randomization helped me avoid habituation and question-order bias. However, because my survey was rather long, it contained some risk of habituation bias.

Another limitation of my survey approach was the potential for wording bias. Although I used a pair of validated survey instruments, the wording of the survey questions was paraphrased to align with a North American aerospace population within the context of OC. To address the risk that I introduced bias through my transcription of the questions, I tried to ensure that the rewording remained faithful to the original intent and that my phrases were neutral. In doing so, I minimized the chance of wording bias so that the participants would not be influenced by the way the questions were phrased.

Significance

A quantitative OC model based on a fractal emergence framework could reduce the subjectivity inherent in contemporary qualitative models. The significance of this study is that it verifies the existence of fractal self-replication and confirms that OC could be correlated with change outcome success in North American aerospace organizations. The results from this study may lead to a validated physics-based framework that provides a predictor of OC outcomes. Moreover, an extension of this work might lead to objective fractal emergence measures generalizable for all industries.

Jabri (2017) characterized OC management as a complex practice that must be understood and managed within the context of the change objectives. The results from my study added to the body of scholarly knowledge by blending the social and contextual aspects of OC with complexity measures previously limited to the physical sciences. Although several scholars had speculated that OC follows a fractal pattern (Joseph, 2019; Malik, 2015), none had studied the quantitative link between fractal alignment and OC success. This study was significant in that it demonstrated that self-replication can be studied quantitatively and is associated with OC outcomes.

Significance to Theory

My research premise viewed OC through the lens of Kurakin's (2011) SOFT. Although fractal theory had been broadly researched in the physical sciences, its use in OC research had been limited to metaphorical or speculative attributions. The current study was among the first of its kind to examine the quantitative link between self-replication as expressed by FD and OC success.

Significance to Practice

Most organizational change efforts fail to achieve their anticipated results (KPMG, 2014). Organizational change denotes an interplay of beliefs and actions between individuals and their structural hierarchies (Leydens et al., 2018). Without a measure of alignment between levels of the organization, leaders cannot determine where to make tactical adjustments to their change management process. My findings may contribute to OC practice by demonstrating whether fractal dimensionality is associated with OC success. A successful, positive association between the FD and reported change outcome success could lead to a practical, real-time measure of OC.

Significance to Social Change

An anterior, concurrent, or posterior measure of change facilitates the ability of managers to influence the OC outcome (Mazri, 2021). I investigated OC through the lens of SOFT and demonstrated that self-scaling behavior is associated with change success. Follow-up research could lead to the development of a quantitative real-time predictor of OC success. This could assuage a portion of the trillions of dollars wasted by organizations failing to implement a change strategy (see Business Wire, 2018). The significance of this study for social change is that a practical measure of OC success using fractals may lead to improved OC outcomes. Less money wasted on failed OC could benefit employment and local reinvestment in the economy (Hans & Vissa, 2021). In addition, this research could improve overall social change research by providing a possible blueprint for applying SOFT to quantify other areas of social research.

Summary

In this chapter, I provided an overview of my study of FD in an OC context. I described the gap in scholarly literature relating to the lack of quantitative studies on OC, especially those evaluating the degree of hierarchical alignment as a factor related to success. I also described the purpose of my research as a means to address the dearth of quantitative research evaluating hierarchical alignment during change. My investigation addressed the relationship between the FD of hierarchical alignment and reported OC success. My research question guided my methodology. In this chapter, I also discussed the types and sources of data and outlined the study’s limitations and challenges. I concluded with a brief summary of the significance of my research to theory and practice, as well as its implications for social change. In Chapter 2, I provide a detailed review of the scholarly literature related to my study. Although few studies included SOFT in OC research, I show that adjacent research in the field supported the general notion.

Chapter 2: Literature Review

Although the field of OC is well-researched, there is very little quantitative information that managers and researchers can use to proactively affect OC success (Harms & Credé, 2010). After more than 3 decades of formal OC research, preengineered change initiatives rarely succeed (Dorling, 2017; D. King & Land, 2018). Bolman and Deal (2017) estimated that two thirds of process reengineering efforts fail because they do not account for the behavioral and human factors that affect OC. Smith et al. (2020) cited the inability to measure change as the leading cause of poor change management. Lindberg (2014) proposed that the lack of practical metrics regarding change reduced the likelihood that an organized change process would be successful.

The purpose of this nonexperimental study was to examine the possibility of OC measurement using a SOFT framework. I attempted to quantify the nature of belief and behavioral alignment across organizational hierarchies through fractal dimensionality. I designed and executed a study to evaluate the quantitative association between a FD and perceived organizational success using a correlational study. In this chapter, I discuss literature supporting the concept that OC emerges as the cumulative result of individual, self-replicating behaviors. I describe how employees' actions and beliefs scale throughout organizational levels to provide a collective force that acts to influence organizational inertia. I refer to this concept as fractal emergence. Although the goal of my research was to develop a fractal emergence theory of organizational change, the scope of my investigation was limited to a proof-of-concept test to determine whether fractal dimensionality was related to OC success. I discuss how scholarly literature supported the notion that the FD is a reasonable measure of self-replication across organizational boundaries. I also discuss how contemporary academic research supported the association between a FD and OC success.

In addition, I describe the gap in scholarly literature pertaining to fractals as an adequate measure of organizational alignment during an OC. Because fractal emergence is a novel theory, very few peer-reviewed literary sources had addressed the quantification of fractal properties within an OC paradigm. However, by evaluating extant OC literature and adjacent research in physics and chaos theory, I present ample support for the fractal emergence premise.

The first section of this chapter introduces the strategy used to find the referenced literature. In the second section, I discuss Kurakin's (2011) SOFT based on the empirical laws of nonequilibrium thermodynamics. I discuss supporting and opposing literature and reveal a gap in the extant understanding of fractal behavior relating to OC. The third section of the literature review consists of presenting and critically evaluating numerous empirical studies related to OC in terms of inertia and motion that support the notion of self-replication as a simplification of complex behavior. In the fourth section of the literature review, I discuss the gaps in contemporary theory and empirical literature. In the fifth section of this chapter, I reconcile the math and physics of change with prevailing OC theory.

Literature Review Method

The literature referenced in this study was selected from several academic databases using Google Scholar linked to the Walden University Library. I conducted additional literature searches using Walden University's Thoreau Multi-Database search. Google Scholar searches yielded numerous results with little granularity concerning specific dates and keywords. My search of *organizational change* alone revealed over 3.5 million results. Limiting the date range to articles published after 1980 resulted in over 1.7 million results, while searching for *fractal theory* in Google Scholar netted over 16,000 results.

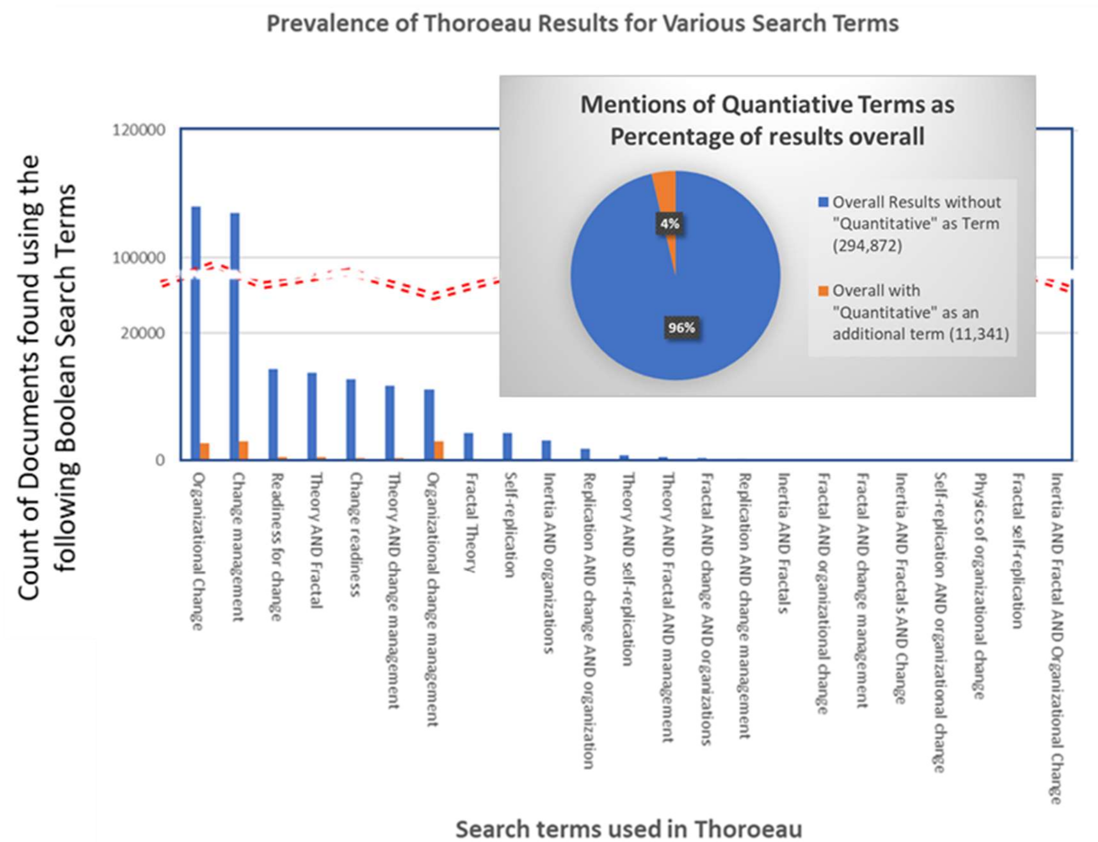
Walden's Thoreau utility provided the ability to add Boolean search strings that confined the literature search results to more manageable numbers. Included in the Thoreau utility was the ability to limit the search to peer-reviewed literature and to select from numerous databases such as ABI/INFORM, Business Source Complete, Cochrane Library, CINAHL, EconLit, Emerald Management, EBSCO, ScienceDirect, JSTOR, PsycINFO, Web of Science, and Walden University. The following search terms were used to identify appropriate literature using the Walden University Thoreau literature search utility, limiting the results to publications after 1980 with full-text results from English language peer-reviewed scholarly journals. The first parenthetical number indicates the search criteria without reference to a quantitative study. Loosely interpreted, this number represents the relative amount of scholarly literature published in the last 40 years on the subject. The second parenthetical number indicates the same amount after the word "quantitative" was added to the search. This value roughly equates to the number of corresponding quantitative studies:

- *organizational change* (108,000), AND *quantitative* (2,763)
- *change management* (107,000) AND *quantitative* (3,016)

- *theory* AND *change management* (11,735) AND *quantitative* (418)
- *organizational change management* (11,195) AND *quantitative* (3,016)
- *readiness for change* (14, 364) AND *quantitative* (490)
- *change readiness* (12,818) AND *quantitative* (447)
- *fractal theory* (4,367) AND *quantitative* (190)
- f*ractal self-replication* (3) AND *quantitative* (0)
- *self-replication* (4,286) AND *quantitative* (114)
- *self-replication* AND *organizational change* (7) AND *quantitative* (1)
- *fractal* AND *organizational change* (53) AND quantitative (0)
- *fractal* AND *change* AND *organizations* (438) AND *quantitative* (50)
- *replication* AND *change* AND *organization* (1,912) AND quantitative (85)
- *replication* AND *change management* (236) AND *quantitative* (110)
- *fractal* AND *change management* (20) AND *quantitative* (1)
- *inertia* AND *organizations* (3,135) AND *quantitative* (85)
- *inertia* AND *fractals* (116) AND *quantitative* (3)
- *inertia* AND *fractals* AND *change* (11) AND *quantitative* (1)
- *inertia* AND *organizational change* (873)
- *inertia* AND *fractal* AND *organizational change* (0) AND *quantitative* (0)
- *theory* AND *fractal* (13,736) AND *quantitative* (504)
- *theory* AND *fractal* AND *management* (603) AND *quantitative* (41)
- *theory* AND s*elf-replication* (832) AND *quantitative* (6)

Figure 1

Graphical Summary Search Results From Thoreau Literature Search



Assuming that quantitative studies were referenced in the search engines using the term “*quantitative*,” I concluded that the number of quantitative studies relating to OC was minimal (see **Error! Reference source not found.** When I looked for terms relating to OC and adjacent topics relevant to fractal emergence, search results including the term “*quantitative*” accounted for less than 4% of the results. Although proportionally smaller, sufficient quantitative sources were available in both management and nonmanagement subjects, making for a robust evaluation of contemporary studies in OC.

A gap in scholarly literature was revealed by reading individual abstracts and sorting the research based on thematic affinity concerning quantitative OC and adjacent topics in self-replication and fractal systems. In the following sections, I show how the inclusion of relevant information within the cited literature supported the notion that fractal emergence would fill a knowledge gap in current OC research. I also discuss how fractal self-replication based on dimensionality is the logical synthesis of current organizational thinking and adjacent physics, mathematics, and chemistry studies.

Self-Organizing Fractal Theory as a Theoretical Framework for OC

In 2011, Kurakin proposed the SOFT based on the empirical laws of nonequilibrium thermodynamics. Kurakin’s work did not address OC. Instead, Kurakin explored the notion of fractals as a means by which to understand and simplify complex behavior in stochastic systems. Kurakin proposed that all complex systems are measurable by considering their use of energy and matter. Kurakin suggested that all systems, including human systems, follow the laws of nonequilibrium thermodynamics. The advantage of exploring OC systems using fractal nonequilibrium thermodynamics is that it allows for the characterization and quantification of the relationships between individuals in an organization as a quantum-level member of a larger organizational supersystem. According to SOFT, OC should be observable through self-replicating behaviors and measurable by considering OC energy or information sinks and sources using self-scaling phenomena (Weber, 2019). A benefit of SOFT is that it contains formulas for characterizing seemingly intractable OC behavior using relatively simple fractal mathematics.

A fundamental tenet of the SOFT is the principle of self-organization and self-scaling behavior. Although I could not find scholarly literature describing the application of SOFT to OC, numerous qualitative studies indicated that self-organization and self-scaling behaviors are present in contemporary organizations. For example, in their study of disaster management processes in information systems, Nespeca et al. (2020) found that self-organization was a common feature in successful management practices across all levels of organizational hierarchy. Another example was Sander's (2017) study of the emergence of the European Union in the context of change management. Sander noted that self-scaling behavior was observable in the transactional cooperation between member nations. Although both papers addressed elements of fractal behavior, neither tied self-scaling or self-replicating behavior to an empirical measure or studied its prevalence as a critical factor relating to successful change.

Management research indicated that organizations demonstrate fractal behaviors, and by logical extension they should be expressible using fractal mathematics. For example, Malik's (2015) work characterized sociotechnical organizations as self-replicating sequences of collective behaviors that repeat and resonate from the individual to the business, economy, and societal levels in a recursive, evolutionary pattern. Malik proposed that the individual acts as a Mandelbrot seed within the organization, setting a recursive archetype through higher levels of organizational abstraction. Joseph (2019) summarized Malik's proposed fractal organization as the collective result of an aggregation of individual behaviors:

> Just as the seed pattern determines the entire structure in the Mandelbrot set, the seed patterns in an individual's outlooks, assumptions, and behaviors (at the individual-level) determine the outcomes at the collective-level. Through the multiplier effect, individual-level actions get amplified to the organizational level. (p. 185)

Although Malik's (2015) work provided a novel metatheory for organizational change based on fractal behavior, it lacked a quantitative measure of fractals. Malik did not provide empirical evidence to support his conclusions or fractal mathematics to support his claims. However, his work was relevant to the study of the fractal nature of OC because it provided a lens through which to view change by considering complex behavior as a fractal pattern. Malik's work was also noteworthy because it was emblematic of the gap in contemporary social research created by the appropriation of a concept from physical science without subsequent supporting evidence. Malik failed to extend the theory of fractal behavior beyond a metaphorical use and failed to provide the means by which to assess his proposed fractal behavior.

In contrast, SOFT provided a means by which to assess fractal behavior. SOFT proposed a common mathematical framework to assess complex systems based on scale-invariant behavior. Kurakin (2011) discussed the application of SOFT theory through a case study of chemical reduction-oxidation (redox) reactions. Kurakin described chemical reactions as systems-level outcomes based on the integrated self-scaling behavior of quantum-level actions. Kurakin demonstrated that SOFT theory builds a calculable link between self-scaling fractals from the quantum level through the astrophysical level. Kurakin indicated that chaotic behavior was an expression of the individual quanta seeking energy/matter balance. Because different levels within the system scale at different rates, Kurakin described why the system appeared chaotic. Kurakin proposed that the overall behavior of complexity is an emergent outcome of self-scaling and self-organizing behavior that is both understandable and predictable. Kurakin described the applicability of SOFT to all naturally occurring systems, including human systems and social networks.

In this regard, SOFT theory addressed some of the persistent gaps in the scholarly literature on OC by providing a deterministic method to quantify how people within a system perform concerning change behaviors or attitudes during or after a change. In SOFT, calculating the degree of fractal behavior could be reduced to a set of relatively simple mathematical expressions relating to fractal dimensionality. However, Kurakin's work demonstrated a knowledge gap in social science research because it had not been applied in OC or social systems. If SOFT was valid for human systems undergoing premeditated change, it should have been possible to measure and quantify OC. To determine whether SOFT applied to OC, it was necessary to consider how well OC research supported the three fundamental characteristics of SOFT systems.

Three Characteristics of Systems in SOFT and Their Application to the Study of OC

Despite the lack of research appraising SOFT in OC, I reviewed the three fundamental characteristics of SOFT to show that there was supporting adjacent research for SOFT applicability to OC. SOFT describes three observable behaviors that are present in complex, natural systems. These characteristics are based on the nature of energy/matter consumption in a system and how energy moves through it. The use of energy is a crucial consideration in the three defining characteristics of a fractal system. Although energy use is considered self-similar across the different energy levels of a system, energy use at any specific time is not necessarily in balance or at equilibrium. Kurakin (2011) posited that the degree of energy consumption within a system increases as system complexity increases, and conversely that energy consumption decreases when complexity decreases. Lind and Sulek (1994) predicted similar behavior in changing organizations, characterizing management energy as an entropic property.

Unlike the physical sciences, where energy is a directly quantifiable measure of work over distance and time, the social sciences can use concepts of organizational work concepts like effort, information dissemination, or belief as an analog to energy. The conceptualization of energy for subjective concepts like belief or information is not unprecedented in social research. For example, IT systems researchers frequently utilized the so-called Maxwell's demon thought model to consider information quality decay using the principles of energy usage and entropy (see Masuyama et al., 2018). Panja and James (2020) modeled the spread of non-factual COVID-19 misinformation based on an energy diffusion model from source to sink. Moreover, Yedidia et al. (2005) showed that belief propagation followed generalized free-energy calculations.

Armed with an understanding of OC energy as work over time relating to human effort, information creation and dissemination, or belief propagation, I reconciled the three thermodynamic characteristics of SOFT to OC systems. The first characteristic of a self-organizing fractal system is that the flow of energy or matter through the interacting constituent elements within the system is interdependent and self-scaling. For the purpose of this discussion, I described this trait as self-scaling flux. The second characteristic of a fractal system is that self-organization results into an interconnected macrostructure. The third characteristic of a fractal system is the correlative relationship between self-organization and energy use. In the remainder of this section, I discussed how adjacent organizational change research supports the notions of self-scaling flux, self-organization, and energy consumption as described by SOFT.

Fundamental Behavior #1: Self-Scaling Flux Across the System

The first distinguishing characteristic of a fractal system is that the energy/matter use within a complex system comprised of interdependent components (or actors) leads to an adjustment to the energy/matter production and consumption rates across the levels of the system. According to SOFT, although energy production and usage rates will vary across the superstructure, a fractal system adapts to the localized energy flux differences across the entire organization. For example, energy overproduction in one area tis balanced by underproduction in another area. If a local area of an organizational superstructure underproduces or overproduces energy, the system responds to accommodate the energy deficit or surplus through the adjustment of production in another area. Alternatively, the system could adapt to the energy flux by working to address the local anomaly. A self-scaling response to energy consumption and production in a human organization could envisioned as changes in policy or management practices to increase productivity or adapt to overproduction.

Overcoming organizational inertia in a human system is synonymous with organizational change (Aksom, 2022). In physics, work is defined as the transfer of energy required to apply a force to an object over a distance, thereby altering its inertia. In the context of organizational change, the transfer of energy to perform work can be conceptualized as the effort required to overcome organizational inertia. Energy flux in OC relates the production and consumption of information and the creolization of beliefs and new behaviors during a transition. For example, Brandtner and Freiling (2021) described how organizational change acts as a force to overcome inertia through the promulgation of learning and unlearning across administrative boundary levels. The concept of energy also applies to the study of beliefs and intents. The creolization and harmonization of cultures during a merger between two companies is analogous to the mixture of two systems with different energy levels that ultimately resolve to a single energy level. Although there are many analogs for energy production and consumption during a change, they are all iterative interactions between the producers and users of the energy. For example, Haken and Portugali (2021) demonstrated that information theory follows free energy and thermodynamic entropy principles and showed that management efforts to maintain informational balance across the organization required effort to maintain a steady operational state. In the case of the Haken and Portugali study, the management response was characterized as a system response to information flux at a lower level of the organization. Although Haken and Portugali did not specifically explore SOFT, their results supported the notion that information can be thought of as a kind of energy that must be balanced across an organizational scale.

Regarding the self-scaling aspect of SOFT, there is substantial academic support for the premise that organizations and businesses are self-scaling based on information flux. For example, Silva and Guerrini (2018) evaluated the role of innovation in organizational change. The authors found that learning was a self-organizing property across the enterprise as new information and behaviors were learned through cyclical and generational learning. Silvia and Guerrini concluded that individual adaptation facilitated organizational learning and behavior that scaled throughout the organizational structure and were observable through congruent and complementary behaviors and practices.

Other contemporary OC studies also explored the notion of self-scaling behavior during a transition. Andrianova et al. (2020) concluded that organizational learning was a social process of self-scaling behaviors that were observable in sociotechnical systems and were expressed through the emergence of fractal patterns. Andrianova et al.'s work was significant to my study of fractal emergence because it hypothesized the link between scale invariant fractal patterns and organizational learning. In finding that organizational learning was expressed as a self-organizing and self-scaling property during change, Andrianova et al. gave credence to the notion that fractal properties could be associated with OC success.

The adoption of new beliefs and behaviors is a form of learning. Many OC change researchers have linked learning and coordination of information and beliefs with organizational success. For example, Jacob et al. (2021) found that interactive collaboration led to ingrained organizational learning within and across organizational levels to positively shape transformations by improving the use of interdependent skills and resources. Studies by Bilan et al. (2020) and Watad (2019) also showed associations between the degree by which the levels of the organization learned and adapted to new behaviors and the resultant OC success.

Kurakin (2011) theorized that all natural systems undergoing change experience some degree of instability as the system scales to meet energy/matter reactions as the gradient emerges. The first tenet of SOFT requires that the rates of energy use (flux) within and across the organizational levels are interdependent and self-scaling. Flux or instability prompts different responses from different system levels within the superstructure and the collective response forms an interdependent network adaptation to the instability. Meske et al. (2020) noted that hierarchical levels tended to impede the exchange of knowledge across an organization but stipulated that communication across domain boundaries created recurring patterns of learning to overcome informational diffusion boundaries. The role of energy as a dynamic flux based on the accumulated beliefs and actions of individuals can be inferred from Schiuma et al.'s (2007) characterization of successful change as the accumulation and fusion of belief-based energy levels across a company.

Dyadic information exchanges are a form of self-scaling flux. For example, Q. Chen et al. (2021) depicted the essential interdependencies between stakeholder and supplier needs during the supply chain process. The authors found that the information exchanged in contractual flow-downs to suppliers served as an enabler to improved information exchange. Q. Chen et al. also found that adaptive feedback from supplier/contractor dyads concerning procedural agreements facilitated stable practices. The authors noted that transference of information and coordination of procedures was an iterative process and recommended that managing the information flux across supplier/contractor boundaries improves overall supply chain performance.

Similarly, Zelt et al. (2018) characterized organizational processes as a collective of repeated patterns of interdependent behavior by individuals relating to an outcome. Zelt et al. demonstrated that the measurement of tasking was not as important as the alignment of individual activities based on the interdependencies of the tasks between workers, teams, and leadership. The hierarchy represents the organization scale in the context of the first characteristic of SOFT. Different layers of the organization produce, consume, and react dynamically to seek energy balance in response to production and consumption. Perhaps the most applicable support for interdependent self-scaling flux within an organizational change is the study by Lawrence and Botes (2011). Lawrence and Botes characterized autopoietic changes in an accounting system based on its ability to make self-scaling changes. The authors noted that autopoiesis followed a self-replicating pattern of change behavior across the organization that they interpreted as an attempt to adjust composition to conserve its boundaries. Lawrence and Botes' study supported the notion that self-scaling responses within organizational levels followed the physical concepts of energy and flux imbalances across hierarchical boundaries.

The idea that different levels of the organization make dynamic adjustments to maintain the flow of work, ideas, and information to maintain stability aligns well with the SOFT notion of energy flux scaling. For example, Dissanayake et al. (2021) demonstrated that leaders and workers tended to work interdependently through their adaptation to information supply and use during IT policy changes. The authors described information flow as a ripple through the organizational levels based on the autonomy given to the actors within each group. Dissanayake et al. determined that adding diversity to the IT governance board helped speed information flow. Ultimately, the Dissanayake et al. concluded that individual autonomy greatly improved organizational performance by improving the quality of information flux between producers and consumers of information. Scaled reactions occur across hierarchical boundaries as individual workers, managers and executives react to and thereby shape information through a series of interdependent interactions.

The Dissanayake et al. (2021) study provided insight into the interdependent reaction to information; however, the authors did not specifically apply the concepts of fractal scaling to their observations. Other scholarly researchers also hinted at the possibility of fractal properties of learning and information flow without specifically fractal mathematics. An example is Nonaka et al. (2014), who described an organizational change in terms of the creation and exploitation of knowledge through a fractal energy/matter continuum. The authors proffered the notion that the establishment of knowledge and its exploitation during organizational change should be observable as fractal patterns that scale from individual to society. Unfortunately, Nonaka et al. described the metaphorical use of fractals as a symbiotic pattern and provided no quantitative evidence to support their claims. Nonaka et al. (2014) described the dynamic nature of information sources and sinks that give rise to non-equilibrium flux between the actors in an organizational system. However, the authors' characterization of OC as a persistent repetition of source and sink for energy across organizational boundaries in the context of knowledge creation is consistent with SOFT's first essential behavior, intimating that energy and matter consumption is a scaling factor in organizational change.

Like the Nonaka et al (2014) study, later work by Weber (2019) showed that information sinks and sources led to event-based nonequilibrium of information that acted as an analog to energy sinks and sources. Weber (2019) revealed that information followed the same fractal patterns described by Nonaka et al. (2014). Weber's (2019) argument was particularly compelling because he expressed information flow using the same terms and properties as those described by nonequilibrium thermodynamics and SOFT.

Parke et al. (2021) also supported the notion of flux-level scale dynamics during organizational change. The authors studied the role of change agent interventions in organizational citizenship behavior and concluded that there are distinct gradients in the power balance during organizational change and when facing adversity. Parke et al. demonstrated that during the early phases of OC, more frequent and more substantive interventions by supervisors or leaders were needed to help the workforce understand and accept the transition. Parke et al. described that in later stages of OC, where individual behaviors and roles became more apparent, the role of the leader became less critical, and peer-level change agents were more vital for change sustainment. The Parke et al. study is significant because it described how an organization comprises interdependent actors who react to and process information at different rates during OC. Based on their beliefs and understanding of the current information, individuals support or hinder the change process through their actions. Parke et al. concluded that information gradients lead to self-scaling change across the entire organizational hierarchy, supporting the first characteristic of SOFT.

The referenced studies show how information, beliefs, intents, and activities serve as an analog to energy/matter use within a complex system during change. Although the studies referenced herein do not specifically prove that SOFT applies to OC, they support the notion of self-scaling, interdependent flux gradients. When considered in aggregate, the cited scholarly literature supports the notion that information, beliefs and behaviors are self-scaling in an organization. However, is change energy is not uniformly created or dispersed during OC, creating a gradient of information and activities that satisfies Kurakin's (2011) criteria for the presence of a fundamental disparity in energy/matter consumption across the levels of the system.

Fundamental Behavior #2: Self-Organization

A second tenant of SOFT is self-organization. Whereas the first SOFT characteristic describes the self-scale responses to energy flux, the second principle reflects how the actors within the system organize in response to energy exchange. Kurakin (2011) proposed that observable macroscopic order was nonlinear across the system superstructure and that the return to stability required a cooperative sequence of actions across domain boundaries. The second behavioral law of SOFT directs that when a system reaches a critical energy/matter flow rate threshold it self-organizes into an interconnected macrostructure.

This second characteristic of SOFT is perhaps the most well-researched phenomenon relating to fractals in social research. Although not necessarily tied to a fractal theory, Walden University's Thoreau database search function returned over 4,000 results for peer-reviewed scholarly journal articles containing references to both self-organization and change. Parke et al. (2021) showed that the levels of an organization dynamically realign through self-organization to adapt to change. However, Parke et al. were not alone in observing that self-organization was a characteristic of OC in complex systems. Haken and Portugali (2021) expanded on the concept of self-organization during OC, concluding that information followed the principles of energy flow and proffered the notion that information systems seek order through self-organization. Haken and Portugali described self-organization as the actions and beliefs of human actors in a complex adaptive system as a requisite practice to seek balance.

Sociotechnical systems theory research is another example of self-organization in hierarchical behavior. Sociotechnical systems are complex interdependent networks of people, decisions, and capabilities dedicated to fulfilling the needs of various stakeholders (Sovacool & Hess, 2017). Sociotechnical systems theory serves as a framework that describes the self-organization of individual actors within a network structure as a means by which to accomplish a task (Naikar & Elix, 2021). Tasking is a means by which a common goal or vision is provided to elicit new behaviors (Steghofer, 2017). Sociotechnical systems self-organize to accomplish the tasking, and by extension, contribute to successful change. Botev (2020) stipulated that self-organization within sociotechnical organizations was required for successful change because the cumulative impact of individual purpose or agency as an influencer of organizational outcomes cannot be pre-planned or managed through top-down control.

A characteristic of sociotechnical systems is their natural tendency to seek stability (Edwards, 2003). Steghofer (2017) characterized modern sociotechnical systems as those that succeed through self-organization by adapting to external threats through OC. In the case of OC, successful change results from the self-organization of beliefs and behaviors and the stabilization of new beliefs and behaviors. A shared vision of the change allows sufficiently motivated and empowered workers to self-organize to accomplish tasking through dynamic adjustments to behaviors and beliefs (Lööw, 2020). Eason (2014) suggested that the purpose of self-organization during change was to seek a sustainable operating paradigm within an evolving interdependent social network. During an organizational transition, there is a constant state of adaption, reorganization, and nonlinear self-organization across hierarchical boundaries (Steghofer, 2017). The notion of self-organization as an enabler in organizational and social change is also prominent in research from Silva and Guerrini (2018), Hagsall et al. (2019), and J. Liu et al. (2021).

Upon consideration of the scholarly evidence for self-organization as an enabler of OC, I conclude that the second fundamental attribute of SOFT is satisfied. Self-organization is an example of the system level management of informational and behavioral energy through the localized organization of the interconnected macrostructure. Zimmermann (2018) suggested that the degree of self-organization during OC was related to the degree by which individuals shared a common vision of the change goal at the superstructural level. A synthesis of Zimmermann's (2018) ideas of self-organization and Haken and Portugali's (2021) notions of energy usage tie the first two tenets of SOFT together and supports the premise that self-organization is present and measurable by looking at the alignment of beliefs and behaviors across the organizational hierarchy.

Fundamental Behavior #3: Energy Rate Flux Balances Across the Scale

The third fundamental principle of SOFT is that the degree of complexity and order within a self-organizing nonequilibrium system is characterized by the rate of energy/matter passing through the system. Kurakin (2011) proposed that the rate of emergent energy/matter flow through the system correlates to the response of the entire system scale in a mutually defining manner. Another way to state the third property of fractal systems is that energy flux cannot exceed energy production. Of the three defining characteristics of SOFT, this principle is probably the least explored in extant OC research. The lack of energy production and consumption research reflects a significant knowledge gap between the social sciences and the physical sciences. However, a closer look at OC research revealed that the conceptual elements of energy conservation and adaptation are present in human systems. For example, Brown et al. (2016) characterized the behavioral alignment of a changing organization in terms of creation, flux, and counter-response. The authors emphasized that the actions of one level of the hierarchy created ripples in other groups of the hierarchy who reacted to the change in a synchronic manner. Brown et al. (2016) failed to describe their premise using physics or mathematics. Still, the authors proposed that a possible measure of OC could be developed by understanding the linkages between information producers and consumers of information along the hierarchy.

A careful review of scholarly literature revealed additional evidence satisfying Kurakin's (2011) third SOFT criteria. Ben-Menahem et al. (2013) characterized OC in terms of strategic renewal based on an organization's absorptive capacity to change and adapt across hierarchical levels. Ben-Menahem et al. measured misalignment between an internal rate of change mandated by the Royal Dutch Shell company compared to the external rates of transformation compared to the overall oil company change. The authors indicated that OC existed as a system that seeks equilibrium through self-organization but is constantly challenged by the rate of emergent change energy demanded by the outside market. Although Ben-Menahem et al. did not specifically consider fractals nor directly described the energy/matter flow within a hierarchy, their work highlighted how complex systems scale throughout an organizational hierarchy in a mutually defining manner. In other words, a complex organization reacts to change in energy with a self-scaling response that is mutually defining across its scale.

A study by Ruben and Gigliotti (2021) highlighted the progression of management research to ideas previously considered the purview of the physical sciences. In their study on organizational leadership, the Ruben and Gigliotti defined leadership as an artifact contextualized by an outcome based on the emergent communication networks established between leaders and followers. Ruben and Gigliotti advanced the notion that information act in terms of energy. The authors described leadership as a dynamic reaction to the ebb and flow between leadership and workers through mutually defining and mutually reinforcing behaviors. Although Ruben and Gigliotti's study did not specifically mention self-organizing fractal theory, it is still significant because it appeared to be the first peer-reviewed journal article that directly described the third principle of SOFT. The authors explained how the measurement of the rate of information passing through the system and modeling of the mutually-reinforcing nature of information learning loops could help characterize seemingly random behavior. However, like many of the articles I have discussed in this section, the authors stopped short of applying systems theory mathematics to their work.

Because SOFT has not been widely evaluated in organizational change, I was not surprised by the lack of published literature describing fractal behavior in organizational research. More research is needed to fully explore the nature of energy and matter flow within an organization undergoing change, and the lack of direct research remains a significant gap in OC knowledge. However, when I consider the adjacent publications describing the three SOFT criteria in aggregate, the connection between SOFT and OC appears to be plausible. There is academic support for self-scaling flux and self-organization, and there is evidence for a correlative mutually reinforcing relationship between energy use and consumption.

Implications of SOFT for the Quantification of Organizational Change

Given that human organizations possess the three characteristics of self-organizing fractal systems, it should be possible to characterize OC through measures related to self-similarity across a hierarchical scale. Using SOFT as a conceptual framework, a changing organization can be described by the degree of self-similarity across its organizational hierarchy. Every fractal system can be characterized from the standpoint of scale and dimension (Chen & Long, 2021). Tao (2017) showed how fractal calculus can describe the activities of discrete (individual quantum) behaviors that scale throughout the organization in continuously operating and dynamic systems. In a human system like a company, the quantum level can be considered the individual actions or beliefs within the networked activities of organizational operation.

Tao (2017) showed that dimensionality measures tie quantum-level actions to collective outcomes through fractal self-scaling properties. Although Tao's approach to fractal calculus is beyond the scope of this effort, his work reinforces the notion that complex behavior in a scaled system can be measured by the assessment of its scale and fractal dimensionality. When viewed through the lens of self-organizing fractal theory, emergent fractal properties should be present and measurable in hierarchies that have undergone or are undergoing a transformation. Extending Tao's (2017) work to OC, I proposed that the degree of hierarchical alignment regarding a specific change initiative was possible using measures of fractal dimensionality and scale.

Therefore, I proposed that if the premise of SOFT applied to OC:

1. Self-scaling behavior could be expressed using a fractal dimension.
2. The fractal dimension is measurable.
3. The FD measure should correlate with the outcome success of the organizational change initiative.
4. Using a fractal measure should greatly simplify the characterization of alignment present in OC, potentially leading to improved mathematical models for OC.

A quantitative measure of self-scaling behavior is important for the advancement of social research. In a review of the time-series dynamics of social systems, Andrianova et al. (2020) stated that the most pressing impediment to social research was the lack of quantifiable methods to measure self-organization. Voss et al. (2017) decried a lack of quantitative research in social science, advising researchers to explore beyond the metaphorical use of fractal self-organization and to instead treat it as a valid physical law that characterizes organizational behavior. Because SOFT describes self-organization in terms of fractal patterns across domain boundaries, a potential benefit of my research is that it could provide a quantifiable measure of self-organization using a fractal dimension. I postulated that if OC follows self-organizing fractal theory, then it should be possible to measure the fractal nature of organizational behavior through the use of FD. The challenge with respect to my research question was to discover whether fractal measures of OC were indicators of OC success.

Importance of a Physical Science-Based Look at OC

My literature search revealed that very few quantitative studies had established a link between quantitative OC measures and outcome indicators. The advantage of a physics-based look at organizational change is that seemingly complex behavior can be understood and expressed mathematically by looking at the alignment and lag in energy and matter through self-similarity and self-replication (Kurakin, 2011). Although energy is often relatively easy to measure in physical sciences, the principles of energy usage can apply to OC. The dynamic nature of change as a flux differential across hierarchical or functional boundaries provides a distinct advantage in my fractal emergence theory. I hypothesized that it might be possible to express progress against change goals by quantifying the degree of belief or behavioral alignment (or misalignment) between hierarchical groups during a change itself.

One possible reason why many contemporary models of OC fail is that they are primarily monolithic and do not account for variation between individuals during the change process. People within a changing organization receive and process information differently and act individually. Different mental models, work products, and behaviors across hierarchical levels can lead to inconsistent behavior that appears stochastic or random when viewed or modelled as monolithic process. Schwarz et al. (2021) characterized the scholarly gap of knowledge relating to the integration of individual and collective impacts on OC failure as one of the most significant knowledge gaps in organizational change research. An advantage of an OC-based evaluation based on physical sciences is that it avoids the analytical need to treat organizations as monolithic entities. A monolithic view of OC cannot account for differences in flux levels across the hierarchy and is therefore limited to inferring broad connections between OC factors and OC success.

For example, Szamosi and Duxbury (2002) studied organizational change success and found that communication, commitment, job satisfaction, and managerial support positively correlated with OC success. Although their work was impeccable from a procedural and analytical standpoint, the Szamosi and Duxbury study exemplifies how some researchers treat an organization as a monolithic entity. It is unlikely that everyone in the organization shared an equal level of the aforementioned factors; therefore, the authors used the mean value reported for each factor to draw broad inferences relating to OC success. The use of a global mean in no way impugned the authors' work. However, the inability to study the dynamics between individuals or groups in real-time confined Szamosi and Duxbury's conclusions to a relatively high-level abstraction.

Szamosi and Duxbury (2002) found that stress, burnout, and change fatigue were negatively associated with OC success. The authors discovered that OC appeared to improve in situations where change management practices were followed, including the communication of change, the consideration of financial strategies regarding the change, and planning the deliberate actions needed to manage the change effort. However, because the change factors were measured using grand mean values, Szamosi and Duxbury could not account for differences across organizational hierarchy during the change. Szamosi and Duxbury's treatment of the OC as a monolith revealed important factors related to change success that ultimately led to other OC studies, including the development of research instruments by Ai et al. (2019) and Li et al. (2016). Both the Ai et al. (2019) and Li et al. (2016) studies were cornerstones in my fractal dimension study. However, Szamosi and Duxbury's (2002) work was limited to retrospective analysis because it treated change factors as a constant across the organization. A monolithic view of OC prevents a researcher from assessing differences related to individual actions or beliefs that occur dynamically during a change. SOFT characterizes a changing system as one in flux based on dynamic adaptation to energy use and production. My interpretation and extrapolation of SOFT applied to OC is that a monolithic view of a dynamically changing organization will never satisfactorily predict change. A researcher using a monolithic interpretation is unlikely to develop a pragmatic measure of OC in real-time. Despite its significant contribution to the field of OC study, the quantitative change model proposed by Szamosi and Duxbury cannot predict successful change, nor can it be used to assess change in real-time.

Although Szamosi and Duxbury's (2002) work helped expand the notion of hierarchical alignment and organizational change, it reflects the current dilemma in OC research. Namely, that change is neither uniform nor monolithic. Hallencreutz and Turner (2011) advocated for improved inquiry within scholarly OC research and specifically recommended supplementing social research using adjacent academic research in the hard sciences. However, Hallencreutz and Turner predicted that people's individual differences and how they perceived their working environment were likely to be too complex to ever be sufficiently described through a static measure. Hallencreutz and Turner's work highlights the problem with current academic research regarding quantitative OC measurement. Hallencreutz and Turner suggested that dynamic measures of change were needed and suggested that researchers turn to adjacent research in physics as mathematics.

Physics-based models for change are becoming more commonplace in extant OC research. Amiripour et al. (2017) portrayed organizational inertia as a path dependency related to its ability to adapt to changing needs. The authors managed to show how vectored quantities could satisfactorily measure the degree of goal accomplishment by an organization. However, the Amiripour et al. study failed to adopt the notion of inertia to lower levels of the organization, nor did the authors provide the supporting mathematics for their claim. Still, Amiripour et al.'s work was significant in that it demonstrated that physics-based concepts relating to OC are beginning to permeate social research.

A physics-based notion of change in social research is vital because it allows a researcher to account for flux and flow of change energy independent of linearity gradients of adoption rates within a changing organization. Although there were no mentions of energy flux through hierarchical scale in my literature search, a study by Naslund and Norrman (2019) introduced and tested a method to measure OC as a function of hierarchical alignment. The authors affirmed that contemporary scholarly research was awash in factors that are suggested to be critical for OC success but opined that very few academic works proactively quantified change. Naslund and Norrman reviewed the Swedish Transport Administration over a two-and-a-half-year period. From their synthesis of the qualitative and quantitative evidence collected as part of their study, Naslund and Norrman constructed a survey to assess the organization's readiness and support for change based on their perceptions from the action research study. The authors applied their measure to several change initiatives that occurred over the study timespan and across multiple levels of the organization. Naslund and Norrman's OC measurement consisted of a change readiness rating, sub-structured with measures of problem clarity, degree of change, internal support, and a common vision for change. The authors proposed that changes in the "before" and "after" elements of their change readiness assessment across the levels in the organization indicated the likelihood of successful OC outcomes.

A significant limitation of the Naslund and Norrman (2019) study was that the authors provided no statistical evidence to support their claims, nor did they establish a control group to differentiate between changes in outcomes and changes in noise factors over the measurement period. Based on the omitted or missing descriptions in the authors' work, I concluded that the Naslund and Norrman article reflected preliminary research to support a theory and that further work was needed to validate the generalizability of their conclusions. Still, Naslund and Norrman denoted the possibility of developing a quantitative measure through the scale quantification of common factors present in OC.

Another noteworthy aspect of Naslund and Norrman's (2019) work was its indirect support of an FD measure of OC using hierarchical alignment. The authors' change measure used hierarchical functions as an analytical pivot by which to measure the penetration of change culture across the different functions within the company. Although the authors failed to quantify hierarchical alignment, their tool showed that the degree of agreement between organizational levels could act as a simplification process in the analysis of OC data. Albeit incomplete, Naslund and Norrman's work was one of the few documented cases where a proposed OC measurement was applied to a change process while the change was occurring. I infer that although management research has yet to fully explore the notion of a real-time OC measurement, a dynamic measurement system should be possible when viewed using a physics-based framework like SOFT.

The Naslund and Norrman (2019) study demonstrated that concepts borrowed from the physical sciences are applicable to social research. However, there remains a disparity between the application of physics-based principles in OC research compared to the other sciences. For example, a Thoreau utility search using the terms "fractal" and "engineering" resulted in over 21,000 search results. My research question reflects my deliberate attempt to establish the viability of a developing a quantifiable link between individual perceptions, actions, beliefs, and OC outcomes. Although no previous social research studies have quantified fractal dimensionality to OC success, some researchers have shown how concepts from physics and chemistry help explain complex or nonlinear behavior.

For example, Axelrod and Axelrod (2017) described a "conference model" of organizational change that introduced the concepts of flux and diffusion into social research. The authors expressed OC as an intervention that affects the entire system rather than a single function. After assessing over 70 OC texts, Axelrod and Axelrod concluded that scholarly literature characterized successful OC as the point at which the organization reached a kind of critical mass to affect change. Axelrod and Axelrod's description of critical mass related to the number of practitioners needed before a change process could become sustaining. Axelrod and Axelrod’s “conference model” described OC as an interaction between individual networks within the organization through a series of workshops intended to have the stakeholders redesign their work to meet the organization’s needs.

Axelrod and Axelrod (2017) provided their framework for conference model change through anecdotal evidence supported by cited research. Although the authors provided no experimental data to prove their theory, Axelrod and Axelrod’s work framed organizations as dynamic systems, which is consistent with the SOFT characteristic of energy use. A salient feature of Axelrod and Axelrod’s work was their characterization of successful OC based on the concerted alignment of the beliefs and actions of individuals in order to achieve a collective change. Lastly, their work highlighted the current conundrum in contemporary social research. Because Axelrod and Axelrod evaluated OC as a monolithic entity, their analytical method could only be applied retroactively, and their determination of critical mass was limited to the size of the organization. By contrast, a SOFT interpretation of change could allow a researcher to evaluate dyadic relations in flux, thereby providing for a proactive, retroactive, or real-time measure of change. SOFT enables real time measures of flux because fractal dimensionality can measure the dyadic alignment itself. Therefore, it is theoretically possible that a fractal measure linking dimensionality to OC outcome could be applied at any point within the OC time spectrum.

Importance of Hierarchical Alignment During Change

A physics-based measure of organizational change should be possible using self-organizing fractal theory. In previous sections, I described that the levels within the hierarchy as an analog to differing energy levels within a changing system. I also discussed how information, actions, and beliefs can serve as equivalents to energy production, usage, and flux. In this section, I describe why the alignment of the hierarchy is a critical characteristic relating to OC success.

Organizational change cannot be successful without the replication of behaviors and information throughout the infrastructure of the company. Pîslă and Muntean (2010) argued that organizational change requires autonomous work units, which they described as “fractals,” to work in concert to align to a specific objective needed to ensure resilience against an external threat. Pîslă and Muntean proposed that chaos theory could account for fractal activities within the company. The authors argued that when properly used in OC research, chaos theory could account for the alignment or misalignment of hierarchies and could be applied to predict organizational change success. Although Pîslă and Muntean’s (2010) work was the first of its kind to bridge the notion of evolutionary theory and chaos theory in the context of organizational change, the authors failed to provide empirical evidence for their framework. Still, their ideas helped advance the notion that seemingly complex organizations can be described using quantitative methods relating to organizational hierarchy with a consideration of the fractal nature of human behavior.

A consistent theme in contemporary scholarly literature that change requires the coordinated efforts of individuals across hierarchies. In the late 1970s, the noted psychologist Dr. James Prochaska published his seminal study of smokers who attempted to change their behavior. Prochaska's resultant transtheoretical model of behavior change theory concluded that real change occurred over time through learned behavior based on individual behavioral choices (as cited by Norcross et al., 2011). Prochaska observed that people do not progress linearly through a change process but alternate back and forth between positive and negative choices (as cited by Biehl et al., 2018). However, Prochaska et al.'s (2020) research provided only observational evidence of the transtheoretical model and presented no suggestions for quantifying the degree of change over time nor measured how well hierarchical levels aligned during the transition.

The nonuniformity of behavior across energy states is a crucial feature of self-organizing fractal theory and is expressed as the nonuniformity of beliefs, behaviors, or information flux within OC research. Although Prochaska's transtheoretical model of change did not provide the quantitative means to measure nonuniformity (as cited by Norcross et al., 2011), his work was significant because it highlighted the importance of hierarchical alignment during the change process. Extrapolating from Proshaska's work, I infer that individuals do not consistently or uniformly perform as expected at all times during the change process, consistent with the basic tenets of adaptation to nonlinear energy flux as described in SOFT.

Consistency of beliefs, behaviors, and information flow across organizational levels is crucial for operational success. Ramirez et al. (2020) characterized inertia as the inability of organizations to adapt to change and found that inertia was a function of organizational complexity and structure. Ramirez et al. showed that organizations comprised of more people and more hierarchical levels were more likely to fail in the change process. In the context of SOFT, more complex hierarchical structures make it more difficult to maintain consistent energy flow across the network. More energy in the form of OC management is required to overcome inertia and promulgate change through complex organizational structures. Gaughan and Bozeman (2016) demonstrated that hierarchical levels significantly influence people's ability to collaborate and affect the power dynamics within and across organizational levels. The authors described hierarchical misalignment as a direct impact on individual behaviors and actions during a change process. A complementary study by Tronvoll et al. (2020) showed that hierarchical coordination during OC was strongly associated with change success and concluded that hierarchies must move together in partnership before OC was sustainable.

The view of informational and behavioral alignment across the hierarchy as a vital factor in OC success was critically important to this fractal emergence study. A synthesis of contemporary OC and SOFT theory supports the notion that organizational change can be measured by looking for the fractal patterns that are present as self-replication across hierarchical boundaries. My research question presupposed that an OC outcome emerges through the concerted, cumulative effects of fractional efforts across the organizational hierarchy.

For me to definitively reject the null hypothesis of my research question, the collective outcomes of emergent individual levels must be present as fractal properties across and within the organizational hierarchy. A collective view of change as an emergent outcome of individual actions is consistent with Weber's (2019) study on information flow in multiplicative ergodic systems. Weber viewed information as a vector-based consequence of individual beliefs and actions based on its location within a social network. While Weber's (2019) theory did not directly support the notion of SOFT behavior in organizational change, it supports the notion that fractal self-replication should be present and measurable within a human system undergoing dynamic behavior.

Review of the Research Questions Relative to Scholarly Literature

My research goal was to determine if fractal self-replication is measurable across organizational hierarchies and to assess whether fractal dimensionality was related to OC success. In the previous section, I described the scholarly support for the notion that organizations undergoing change meet the three fundamental criteria described by SOFT. Through the logical application of self-organizing fractal theory, I proposed that there should be a relationship between fractal dimension and OC outcomes. Specifically, I sought to determine whether hierarchical alignment is expressed through its fractal dimension based on the degree of self-replication across hierarchical boundaries. Using the derived value of hierarchical alignment measured as a fractal dimension, I planned to ascertain if there was a correlation between fractal dimensionality and OC success. My research question was:

RQ: Is there an association between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success?

H_0: There is no correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

H_a: There is a statistically significant correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

The answer to my research question could help close the knowledge gap in extant research by exploring the nature of fractals within organizational change studies. My approach to answering the research question was similar to the method used by Hassan et al. (2013) to model self-replication of stochastic Brownian particles undergoing consolidation. However, I could not find any studies that attempted to apply fractal dimensionality measures to organizational change in a search of contemporary OC research.

Although my research question was novel within the context of OC, there was sufficient scholarly literature suggesting that the use of fractals applies to sociotechnical systems like aerospace organizations. For example, Nuhfer (2017) also supported the use of fractals in human systems as viewed through the theoretical lens of chaos theory. In particular, Nuhfer characterized learning outcomes based on the “butterfly effect,” resulting from hundreds or thousands of minuscule-sized behaviors that tend to aggregate to create complex outcomes. Nuhfer suggested that even though any individual behavior was ephemeral and statistically improbable, its presence in concert with other improbable actions inexorably led to a “likely” outcome. Nuhfer described learning as an analog to organizational change and characterized education as a form of the butterfly effect, seeking to make minuscule changes in students' perceptions of truth and beauty. The author suggested that changed perceptions led to new ways of thinking. Nuhfer described his butterfly effect concept as a self-propagating fractal pattern of synergistic behavior across multiple levels of ambiguity within a complex system.

One of the shortcomings of Nuhfer's (2017) work is that it provided no empirical evidence to support its ideas, nor did the author cite scholarly work to support his premise. Nuhfer acknowledged the quantitative limitations of his research in his report and compared his epistemic principles to Wegener's first suggestion about the existence of plate tectonics, which at the time was an unproven premise based on anecdotal evidence. Certainly, Nuhfer's work is not proof of the fractal emergence concept; however, Nuhfers, conclusions reflected the potential for fractal mathematics to capture organizational behavior and exemplified the gap in scholarly literature linking fractal theory to social research. Nuhfer advocated for more fractal analysis in human systems and suggested that researchers first look for simple fractal patterns before venturing into more complex chaos theory research.

Nuhfer's (2017) work underscores the general problem regarding the use of fractals in OC research, which is that many authors have discussed fractal behavior in the metaphorical sense, but none have applied the concept quantitatively. Another example is Mollenhauer's (2017) research. The author discussed the complementary nature of chaos theory and fractals as a means by which irregular patterns of human behavior could be described in mathematical terms. Mollenhauer described fractal behavior as a logical and necessary part of OC research but failed to extend the premise beyond a metaphorical concept. Mollenhauer's work summarized extant chaos theory and fractal applications for orthodontia; however, his work was beneficial to my study because it supported the notion that complex, nonlinear behavior can be expressed through quantification fractal terms. Mollenhauer suggested that fractals could be used to express the nonlinear nature of the interactions between complex factors. Mollenhauer portrayed human organizations as subject to the laws of physics, like force, energy, and inertia.

The prospect of utilizing chaos theory to organizational change research can be considered a daunting task because of the complexity of measuring and modeling individual interactions. Mollenhauer (2017) cautioned that because human actions appeared to be inherently chaotic, the attempt to measure human behavior using fractals could result in an inconclusive prediction of outcomes. However, an advantage of a SOFT-based view of OC is that it does not require the individual measure of each action. The presences of scale invariant behavior denotes that a researcher only needs to measure the degree of self-similarity of energy usage across boundaries to identify the transactional efficiency of the individual operators within the system (Kurakin, 2011). Although Mollenhauer (2017) did not refer to SOFT in his research, he conceded that while specific organizational results were generally unpredictable, that it was possible for researchers to find a satisfactory quantitative relationship between initial conditions and probabilistic change outcomes.

A physics-based evaluation of organizational inertia allows a researcher to regard organizational change as an unbalanced force that overcomes operational inertia and moves organizational practice from its vectored trajectory (Aksom, 2022). A physics based view of OC helps a researcher explain the criticality of the individual worker's role in providing the energy needed to overcome inertia. Adapting Newton's first law of motion, the larger the organization, I conclude that the greater its organizational mass, and the more likely it will remain along its current operational path unless an unbalanced force is applied. If I adapt Newton's second law of motion to OC, the bigger the organizational mass, or the more radical the change required, the more force needed to move the organization. Individual workers and managers constitute an incremental change force during OC that accumulates to produce an OC outcome. If the workers' intent to change is opposed to leadership's desired to change, I believe that it is reasonable to expect that the leader's actions will counteract the change and lower its chances of success. Upon consideration of the literature, I discussed in this chapter, I surmise that the more aligned the worker and management change forces, the more likely the OC will be successful. In the context of SOFT, I infer that the actions resulting in change must align across the organization in self-organizing, resulting in measurable self-replicating patterns in order for a change force to overcome organizational inertia.

The notion of a physics-based look at alignment as an indicator of energy contributing to change force is supported by Stone's (2010) research. Stone described successful OC as the accumulation of small incremental changes and postulated that smaller objectives achieved over time were easier to achieve. Anecdotal proof for the importance of small changes and organizational alignment during transition is also described in scholarly OC literature. For example, the transformational power of individuals working in a concerted effort to achieve change is at the heart of practices like agile transformations (see Žužek et al., 2020) and Kaizen management (see Mendez & Vila-Alonso, 2018). However, being aware of organizational inertia and being able to measure it are distinctly different challenges.

Measuring Fractal Behavior in an Organizational Social System

In the previous sections, I discussed the gap in scholarly literature regarding a quantitative measurement of organizational change. I reasoned that fractal mathematics could be used to simplify the quantification of seemingly chaotic systems like large, complex organizations undergoing change. I fashioned my research question to evaluate whether measurable fractal patterns are present across hierarchical levels and if the fractal dimension was an indicator of organizational change success. My research design tested for an association between fractal properties and OC success. Ultimately, the study of fractal dimensionality is only a small part of a more extensive application of a SOFT-based fractal emergence study. If SOFT theory applies to OC, it is theoretically possible to construct an interactive network model based on fractal measures of change factors in real-time. A comprehensive SOFT-based network model that could proactively assess alignment as it emerges in real time and identify where to apply management attention. A real time measure of change is the ultimate goal of a fractal emergence line of inquiry. However, for fractal emergence network models to be possible, I must first establish if fractal dimensionality is related to change success. A comprehensive fractal emergence model for OC is outside the scope of this effort, which was limited to exploring the association between FD and OC success. However, a successful answer to my research question may provide the proof-of-concept necessary to support a larger fractal emergence framework of OC, and the use of FD to measure alignment is supported by contemporary social research.

Case for Fractal Dimensionality and Scale

I posed my research question to test if fractal modeling of self-replication across hierarchical boundaries was indicative of OC success outcomes. My inquiry was limited to association, not causality. My approach was similar to the approach used by Hassan et al. (2013) to model the self-replication of stochastic Brownian particles undergoing consolidation. A notable difference between my study and Hassan et al.’s approach to modelling the mathematics of Brownian particles as a predictive equation is that my research question was limited to the correlative expression of fractal scale and dimensionality as an indicative factor in OC success.

Scale and dimensionality are essential concepts when looking for fractal behavior in human systems. For example, Mosteanu et al. (2019) studied the nature of financial patterns related to management decisions. The authors noted a distinct fractal pattern to seemingly stochastic systems like stock market trends and investors’ approaches to market information. The authors described the presence of self-scaling behavior that only became apparent when looked at through the lens of fractal mathematics. Mosteanu et al. described their observation as a pattern with internal homothetic properties, indicating a repeated shape with the same basic form but on different time scales. A primary conclusion of Mosteanu et al.’s findings was that financial patterns repeated in a way that has the characteristics of self-similarity in scale and dimension.

The characterization of fractal dimension simplifies the process of assessing the organizational hierarchy for signs of self-organization and replication. Vakili (2018) characterized fractal systems as complex nonlinear systems that become self-organizing based on replicating behavioral patterns that emerge based on the interdependencies between the actors within the system. Vakili stated that fractal systems appeared chaotic because they did not generally perform as correlative, linear responses to stimuli. However, he claimed that such systems tended to show deep levels of pattern repetition that gave way to a structured order that follows generalized attractors attributed to beliefs or perceptions. Vakili asserted that the nonlinear and self-replicating response to stimuli was analogous to the behaviors of living systems and affirmed that complicated behaviors were characterized through simple fractal scale and dimensionality. Vakili described how the individual components from the quantum level up to the universal level could be understood through fractal modeling, even if the model could not be used to inform users well enough to design the system from scratch. Vakili proposed that fractal dimensionality and scale helped predict behavior even though it was insufficient to help researchers anticipate all aspects of its evolution.

Scholarly literature supports the notion that organizational alignment during change is related to achieving a collective vectored outcome. Vectoring is a crucial part of physics-based modeling because it refers to the aggregate magnitude and direction of a collective set of individual elements, each with its own magnitude and direction (Das et al., 2019). Qiu et al. (2020) found that the expression of group dynamics through vectored mathematics relied on the quality of the individual and organizational dynamics, which ultimately related to the perceptions of the cumulative value perceived by the organization. The Qiu et al. study relied on replicated model iterations to account for individual variations in alignment instead of fractal calculations. However, their work exemplified how mathematical vector alignment considerations are crucial to predicting successful change. Because inertia is related to alignment across the organization, scale and dimensionality are critical considerations for fractal systems. My inquiry served as an alternative to iterative modeling and attempted to quantify OC alignment through fractal dimension and scale.

Voss et al. (2017) regarded the fractal characterization of OC as a logical consequence of naturally occurring self-similar patterns of behavior ascertained through quantitative measures. The authors posited that social research has been slow to understand how fractal dimensionality could be applied to simplify the measurement of change:

> Since Mandelbrot's discovery of fractality as a mathematical property of structuration in nature, the study of this phenomenon in the context of human organizations has proceeded slowly and speculatively for the most part…. Despite the difference in complexity, fractal processes in human organizations are fundamentally the same as those in the natural world. As a basic principle of human self-organizing, it is ordinary rather than novel, common rather than rare, and ubiquitous rather than idiosyncratic. Indeed, a fractal conception of human self-organizing reveals the physical laws underlying human organizations… Fractality removes the mystery from questions of organizational development,

> demonstrating lucidly where the difficulty in managing organizational change resides and laying a basis for addressing it rationally (Voss et al., 2017, p. 1).

Scholarly Support for My Approach

If SOFT applies to human systems as it does to chemical systems, I reasoned that the prospects for characterizing OC success using fractal dimensionality were promising. The fractal dimension indicates how many copies or duplicates will be observable on a given scale (Lumen Learning, n.d.; Shi, 2013). In the field of pixel analysis used in optical imaging, the higher the fractal dimension, the finer the photographic texture (Schowengerdt, 2006). I inferred that the FD level of fine vs rough would also apply to human systems and could be used to indicate the degree of alignment or misalignment between hierarchical levels. For example, Lueg (2018) demonstrated that misalignment between power levels within organizations as individuals exchanged information and completed tasks created a frictional force that lowered the organization's overall efficiency. Extrapolating from Lueg's work, organizational alignment expressed as a FD based on the degree of agreement between workers and leaders during a change could be synonymous with organizational change friction and lower the likelihood of OC success. However, OC friction measurements were outside the scope of this study. However, by establishing an association between FD and OC success, my study could enable future, more expansive fractal studies of OC friction and inertia. A verification that FD applies to human systems in this study could become a steppingstone to more advanced OC research, in the same way that FD related to self-similarity in pixel comparisons led to improved photographic image analysis.

Schowengerdt (2006) described dimensionality as the key to understanding complex system behavior. His work showed how fractal objects could have non-integer, or intermediate dimensionalities, such as 1.3 for an irregular line or 2.7 for a photographic image "surface." H. Liu et al. (2020) described a similar use of fractal geometry using photographic analysis. H. Liu et al. (2020) explored the use of fractal geometry to characterize neuroimaging of patients based on their age. Using fractal dimensionality, the authors demonstrated significant age-related declines in many of the measures attributed to reductions in cognitive functions.

Although my study did not produce the same range of intermediate fractal dimensionality as the Schowengerdt (2006), nor did it describe neurological changes like the H. Liu et al. (2020) study, both studies underscore the importance of measuring dimensionality to assess complex associative relationships. A fundamental premise within SOFT is that differences relating to outcomes can be expressed through differences in self-replicating patterns. I designed my study to determine if differences in the degree of self-replication of beliefs and behaviors during change across hierarchical boundaries alignment were also indicative of OC outcomes. Like the Schowengerdt or H. Liu study, I hoped to demonstrate that relative hierarchical alignment differences were associated with OC outcomes, thereby establishing the applicability of SOFT to OC.

Although I could not find any published organizational change studies attempting to quantify fractal dimension and scale with organizational outcomes, there were several examples of quantitative social research exploring the association between OC criterion variables and successful OC outcomes. Most used a survey instrument to assess a self-selected study sample of a larger group or organization. I also used a survey instrument to conduct my study.

My use of a survey tool to quantitatively assess a broad and often disparate culture is supported by scholarly research. For example, Pihlak and Alas (2012) studied the nature of organizational change success as a function of leadership style in Indian, Chinese, and Estonian organizations. Pihlak and Alas used an interview questionnaire developed by Andreeva (2008) to assess the relationship between management style and its impact on OC behavior in different cultures. From an interview of 177 individuals from three different countries, Pihlak and Alas (2012) successfully determined the correlation between different leadership styles and OC success. Pihlak and Alas found that the participative level of employee involvement during change was positively correlated with a successful change outcome in India and Estonia. The Pihlak and Alas study was also significant to my study because it confirmed that survey-based correlative studies could account for the disparity in cultures and were sufficient to characterize OC success.

Deni et al. (2020) also provided evidence that a quantitative survey study can provide correlative proof of causality relating to OC success. Deni et al. studied how knowledge management practices correlated with innovation capability and business performance. The Deni et al. study reaffirmed my literature search conclusion that there was a paucity of quantitative research linking organizational change factors and resulting OC success. Deni et al. evaluated a 20-item questionnaire to derive critical success and knowledge management factors for business outcomes. Deni et al. validated their factors and responses using confirmatory factor analysis (CFA) and then created a structural model (SEM) equation linking the characteristics to perceived outcomes. Although many details are missing in Deni et al.'s work, particularly in their sample size and their basis for structural modeling, their paper represented one of the first attempts to model organizational change mathematically using regression and correlation. The Deni et al. study was significant to my research because it demonstrated both a quantitative exploration of OC change factors and success, but also demonstrated how structural equation modeling could be used to confirm the validity of survey responses. The Deni at al. study helped serve as a guide for my retrospective CFA of my completed survey dataset.

How to Measure Alignment Using a Survey Instrument

Measuring fractal emergence through self-replication is a novel concept in organizational change theory. My research question was novel and lacked an available FD survey or OC measurement instrument to assess fractal dimensionality. However, organizational change has been widely researched, and there are many studies and research instruments available to measure the alignments of beliefs and behavioral intent relating to OC. In this section, I describe why I selected two specific survey instruments to measure alignment in beliefs, actions, and attitudes toward organizational change. Although neither survey instrument was designed to explicitly measure dimensionality in North American aerospace organizations, they were easily adapted to allow for FD measurement.

Ai et al. (2019) created and validated a survey instrument to measure the dispersion of cross-cultural changes throughout a social network or organization. Ai et al. characterized creolization as an emergent state resulting from exposure to a new operating paradigm, citing IT outsourcing as an example case. Ai et al. argued that IT outsourcing was a fundamental indicator of creolization rates because it involved synchronizing different work packets over significant geographical, temporal, and cultural divides. The authors described creolization as the ability of disparate groups to develop working cross-cultural relations and establish a consistent process in response to the emergence of change resistance resulting from the cultures. Ai et al. affirmed that their survey was created because of the lack of quantitative measures in organizational change. Because creolization is synonymous with adapting and harmonizing cultural attitudes and behaviors during a transition (Hower et al., 2019; Pervukhina & Lysova, 2021), it was an appropriate tool for organizational change study.

Ai et al. (2019) contextualized dispersion rates across the individual, project, and organizational dimensions as a creolization process. Although the authors were not specifically investigating organizational success, they measured the degree of creolization change and harmonization. Ai et al. proposed that their cultural hybridity survey questions directly assessed the conformity of purpose given a common task. Because the conformity of purpose aligned well with the hierarchical alignment of purpose in OC, the use of the authors' survey instrument was ideal for my study.

Ai et al. also evaluated boundary spanning and identity multiplicity as critical factors relating to creolization. Boundary spanning relates to the efforts to connect different levels in a network to work more seamlessly (Cao et al., 2021). Boundary spanning also refers to the effort required to harmonize OC efforts across organizational hierarchies (Tasselli & Caimo, 2019). In the context of SOFT, boundary spanning can be viewed as the energy expended to adapt and regulate the production and consumption flux across an organizational boundary. Fang et al. (2021) demonstrated that boundary spanning is an enabler of successful change and improves employee morale and communication. Therefore, boundary spanning is an important factor in OC and was suitable for inclusion in my survey instrument.

The Ai et al. survey also assessed identity multiplicity. Identity multiplicity refers to the ability of an individual to maintain multiple and distinct personas to understand different perspectives (Stasulane, 2021). Identity multiplicity in OC helps individuals overcome their old mental models of behavior in favor of preferred or new behaviors (Gaither, 2018). Breaking down old mental models and reforming new ones enable organizational learning and support positive business outcomes (Senge et al., 2014). In the context of SOFT, identity multiplicity can be equated with the second fundamental principle of complex system, when the actors within the system organize in response to energy exchange to reach a new equilibrium state.

Ai et al.'s (2019) survey instrument was highly relevant to my study of fractal dimensionality and OC success. Although the authors studied cultural hybridization and creolization, the factors Ai et al. evaluated enabled them to measure the degree of alignment to organizational goals. By adding demographic information about a respondent's level within the hierarchy, I was also able to measure how well each organizational level worked within and across its hierarchical boundaries.

Ai et al.'s (2019) survey questions were written using the nomenclature and phrasing relevant to IT professionals in a global business. I rephrased their questions without altering their intent to adapt them to a North American aerospace community. However, the analysis and structure of the authors' creolization instrument enabled me to determine if the calculation of a fractal dimension was viable based on beliefs and attitudes towards the change. The Ai et al. survey instrument permitted me to identify and compare the level of cultural hybridization perceived in the workforce regarding a specific change initiative. By equating creolization with the adoption of new practices through a change initiative relative to the respondent's level within the organization, I was also able to quantify the dispersion and self-replication of behaviors across the organizational hierarchy.

Ai et al.'s (2019) survey contained several questions relating to interactions with peers and management and enabled the quantification of attitudinal and belief-based alignment across the hierarchy during change. Pilgrim et al. (2020) described the organizational change process as an interacting power structure of influence and action that is aimed at breaking old decision patterns and establishing new ones. Pilgrim et al. explained that organizational transformation is difficult because individuals within the organization must simultaneously think and act in a new way that aligns across the organization. A study by Schweiger et al. (2018) concluded that OC can only be successful when all groups at all levels of the organization are aware of the need to change, understand what needs to change, and feel safe in making the change. Therefore, for my survey to capture fractal dimensionality must also have the ability to measure how people within the organization were thinking and acting during the change process relative to the OC goals. In that regard, the Ai et al. instrument was suitable for my research purpose.

Because beliefs, attitudes, and behaviors across hierarchies are analogous to nonlinear energy flow through a system in an attempt to maintain system stability, the Ai et al. creolization instrument was consistent with SOFT concepts. However, SOFT concepts also include the use and production of energy, which is analogous to behavioral intent and actions. The Ai et al. (2019) instrument captures beliefs and interactions but does not fully describe the intents and actions of the participants during the change. Therefore, I needed a supplemental research instrument capable of measuring the resistance to change or the intent to change behavior.

Change resistance is well-documented in scholarly literature, and the degree of resistance to change is an essential component of change behavior. For example, Pfaff et al. (2019) found that an individual health care worker's change resistance was directly correlated with the hospital's changed performance. However, the nature of the Pfaff et al. investigative process obviated the researcher's ability to prove causality, nor could it resolve whether attitudes caused poor performance or if poor performance caused negative attitudes. Rafferty and Minbashian (2019) examined change resistance and found that employee beliefs and positive emotions combined with change acceptance proxied as an indicator of successful change outcome.

Resistance to change is more than a belief or acceptance. For change to succeed, individual and collective behavior must change. Spaulding et al. (2017) found that a healthcare organization's capacity for change was directly related to the workforce's capacity to perform new work. The authors demonstrated that a low readiness to change resulted in change resistance and translated into a high likelihood of OC failure. Change intent, or resistance to change expresses how an individual intends or intended to perform. Organizationally, OC cannot successfully occur until the cumulative vectored actions of the organization overcome the organizational inertia resisting the change process.

I selected Li et al.'s (2016) survey to capture change resistance to supplement the Ai et al. (2019) creolization instrument. Li et al. studied resistance to change during the implementation of a knowledge management system. The authors noted that an individual's tendency to resist knowledge management systems led to inertial resistance to change at the organizational level. Li et al. characterized inertia as the tendency for beliefs and behaviors to endure once formed, making it a fitting supplement to the Ai et al. (2019) study of creolization.

Li et al.'s (2016) research resulted in a quantitative instrument to measure OC attitudes and gauge individual change resistance behaviors as an expression of cognitive inertia. The authors proposed that the concepts of status quo bias and cognitive inertia were causally linked to change resistance and correlated with outcome success. Li et al. found a positive correlation between inertia and the intention to resist knowledge management systems. Li et al. also found that change resistance persisted inconsistently across hierarchical levels during the change process. Although energy flux is expected in SOFT, organizational alignment of energy across hierarchies was not Li et al.'s expressed research intent However, because behavioral intent can be considered a form of energy in the context of SOFT, by adding a demographic questions about the hierarchical level of the survey participant, the Li et al. instrument was ideal for capturing behavioral intent and the degree of self-organization across the organization using a FD. Ultimately, Li et al. characterized organizational cognitive inertia by assessing loss aversion, transaction costs, social norms, behavioral patterns, change attitudes, and cognitive intentions to resist change, reasoning that the results were more generalizable to resistance to change.

A salient feature of the Li et al. (2016) survey instrument is that it complemented the SOFT notion of inertia in terms of action and intent as a flux across an organization undergoing change. Ai et al.'s (2019) survey described a cultural transformation of beliefs and values across hierarchies. A fusion of the two surveys provided the hierarchical information I needed to assess fractal dimension during OC. Like the Ai et al. creolization survey, I rephrased the Li et al. survey questions from their original applicability to a knowledge management system change to a suit more general OC purpose.

Conclusion

Black and La Venture (2018) described organizational culture as an amalgam of human beliefs, decisions, and sociological exchanges. Although the field of organizational change has been extensively studied, more than 50% of all transformative efforts fail to achieve their anticipated results (KPMG, 2014). Perhaps the lack of OC success is related to the inability to measure OC success in real-time. Without a measure of alignment between levels of the organization, leaders cannot know where to make tactical adjustments to their change management process. Change measurement is particularly challenging in North American aerospace companies due to the complexities of rapid technology changeover, security concerns, and the availability of operational data relating to change (Kattner et al., 2018). This literature review revealed a significant gap in contemporary social research relating to quantitative expressions of organizational change. As shown in the literature review, quantitative research that does evaluate organizational change is limited by monolithic expressions of the organization. As such, it lacks the fidelity to assess the OC effort until after it has concluded. Perhaps the application of complementary physical science research in fractal mathematics can reveal new insight into quantitative OC measures.

Kurakin's (2011) self-organizing fractal theory provides a physics-based view of complex systems that establishes a means to measure behaviors by searching for self-organization and self-replication across different layers of abstraction throughout the system. SOFT provides a theoretical lens for researchers to view complex behavior through a dimensionality simplification underlying alignment. Specifically, SOFT theory simplifies complex behavior by considering self-replication and self-scale. Although there are currently no studies linking SOFT to OC, numerous adjacent studies indicate the presence of SOFT characteristics during the change process. Contemporary social research is replete with studies that highlight the importance of hierarchical alignment during organizational change. I crafted my study to combine the well-established qualitative knowledge about human systems provided by social research with the quantitative aspects of the physical sciences, particularly physics and complexity theory research related to fractal mathematics and fractal dimensionality.

The lack of research exploring the nature of fractals in organizational change represents a significant knowledge gap in scholarly change research. However, careful consideration of published research provides clues that lead me to believe that fractal properties are present in changing human systems. The benefit of a physics-based view of organizational change is that it helps explain nonlinear behavior based on non-equilibrium thermodynamics. SOFT provides both a philosophy and method to understand and quantify hierarchical alignment through the measure of dimensionality and scale. The foundation for SOFT is well supported by contemporary research, but more work is needed to fully develop the theory and test if dimensionality is related to change success.

This literature review highlights the broad gap in scholarly knowledge concerning fractal behavior during change when considered a whole. Like those exploring Prochaska et al.'s (2020) transtheoretical model of behavior change theory, many studies have stressed the importance of individual behavioral choices as the quantum-level contribution to an aggregate organizational outcome. Studies like those of Voss et al. (2017) have intimated that fractal dimensionality can be used to measure OC. However, no current social research has quantitatively explored the use of fractal dimensionality during the change process. A consideration of contemporary social and physical science research supports the notion that each of the required elements of Kurakin's (2011) SOFT theory is present and should be measurable in organizations.

The last part of this chapter described how two contemporary survey instruments were appropriate as a means by which to collect data about organizational change that supports fractal dimension and scale calculation. A modification of two existing survey instruments allows for the measurement of hierarchical alignment in a way that is amenable to the use of fractal dimension. I discussed how Ai et al.'s (2019) creolization survey addresses change inertia and aspects of hierarchical alignment. I also showed how Li et al.'s (2016) survey allows for measures of the inertial factors relating to OC attitudes and change resistance regarding the relative intent to change. When considered collectively, an amalgam of both survey instruments satisfactorily addresses SOFT energy flux in terms of beliefs, actions, and behaviors across hierarchical boundaries and provides relevant data needed to determine fractal dimensionality and scale.

Chapter 3: Research Method

The purpose of this study was to explore whether fractal patterns of beliefs and behaviors across organizational hierarchies were indicators of OC success. If fractal emergence was discernible through self-replication, I proposed that the findings could reveal whether fractal patterns were associative indicators of OC success. This research project was a nonexperimental quantitative study using survey responses from North American aerospace workers. A quantitative approach was appropriate for the research purpose. I sought to establish a statistical link between the degree of hierarchical self-replication and OC success. In this chapter, I describe the methodology of my study and substantiate my use of a survey research instrument as the optimal means to answer the research question. I address my methodological approach in five sections. The first section provides an overview of available research approaches and a discussion of quantitative methodology's relative merits and appropriateness to answer my research question. I then consider the available quantitative designs and their suitability to answer my research question and discuss why my design choices were the most appropriate for my inquiry goals. The second section presents my experimental method, including sample size considerations and procedures to recruit participants. I also discuss the instrumentation and operationalization of the variables I used in my instrument. Following the methodology review, I discuss my data analysis plan and describe my plans for determining the FD. The fourth section addresses the threats to validity relevant to my methodological choices. The final section concludes with a summary of my methodological design.

Research Design and Rationale

I used a quantitative, nonexperimental correlational design to examine the relationship between FD and OC success. A correlational design allowed me to compare groups of variables. The predictor variable in my study was the derived FD, and the criterion variable was the perceived OC success. I used a survey instrument to measure the degree of self-replication within organizational hierarchies based on the mean individual response regarding organizational creolization and resistance to change measures against the mean attribution of OC success. I solicited and surveyed employees within North American aerospace companies who had recently completed or were in the process of completing an OC.

After gathering the survey data, I computed the FD for hierarchical alignment based on the degree of agreement to thematic questions based on hierarchical dyadic pairings. I then determined whether the FD was associated with the reported OC success. Curtis et al. (2016) described correlational research as an appropriate method to explore predictor–criterion relationships in social science research because it can assess the strength and direction of the relationship between predictor and criterion variables. The results obtained from the current study helped address my conceptual proposition concerning the construct relationship between fractal dimensionality and OC success. The results allowed me to quantitatively answer my research question and provide for an unambiguous adjudication of my research hypotheses.

The research question and hypotheses for my study were the following:

RQ: Is there an association between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success?

H_0: There is no correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

H_a: There is a statistically significant correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

Because correlation studies are bidirectional (Burkholder et al., 2016), the measure of association indicates how changes in the predictor variable are associated with changes in the criterion variable. Based on my research question, the calculated FD was the predictor variable, and the participant's description of OC success was the criterion variable. I conducted an online self-administered survey over 31 days to gather the data needed for my study. I recruited survey participants through the social media websites LinkedIn, SurveyCircle, Facebook, and the Walden participant pool. I used a quantitative, nonexperimental research design with a descriptive correlational method of analysis.

Overview and Selection of Methodologies

The three commonly performed research methodologies for social science research are quantitative, qualitative, and mixed methods. I discuss each approach and its relative strengths and weaknesses regarding my research goals.

Characteristics of Quantitative Research

Quantitative research is a broad term for describing numerical analysis to answer a research question. Quantitative methods are associated with a positivist epistemology that presupposes that data analysis can extract meaning from numerical values (Slevitch, 2011). Quantitative methodology is used to measure and analyze relationships between variables to make sense of phenomena free from emotion or subjective judgment (Abu-Alhaija, 2019). Because quantitative methods allow for descriptive or predictive analyses to ascertain statistically significant relationships between variables and responses (Perl & Noldon, 2000), the quantitative approach was best suited to address my research question.

I measured fractal dimensionality across hierarchical boundaries based on Likert-scale responses from survey participants and computed the statistical association between fractal dimensionality and OC success. I was not looking to address why there would be fractals or how people perceived self-replication; instead, I sought to eliminate subjective factors in favor of objective ones. Burkholder and Burbank (2019) described the etic nature of quantitative research as the conviction that knowledge can be generated through facts derived from applying scientific methods and practices. The nature of my effort was quantitative because I sought to compute fractal dimensionality using SOFT from an objective perspective.

Although quantitative methodology was suitable for my inquiry, a quantitative inquiry must be carefully managed. The selection of a quantitative experimental design invokes a style of reasoning that presumes an objective reality that can be measured and quantified in a meaningful way. Zyphur and Pierides (2020) warned that quantitative methods could become a self-vindicating style of reasoning that presumes what is real and how it can be observed. Rijgersberg et al. (2009) warned that quantitative analysis without contextual metadata provides the illusion of objectivity but risks creating a bias in the results despite its reproducibility. Although my research question was objectively framed, I was careful to include sufficient descriptive data and the conditions of the data gathering and analyses to minimize cognitive bias (see Rijgersberg et al., 2009).

Characteristics of Qualitative Research

At the ontological level, qualitative research is the search for meaning in human behavior. Crossman (2020) characterized qualitative research as an emic practice to investigate the meanings people attribute to behavior and understand social and behavioral truths through observation and ascription of meaning to those observations. Abu-Alhaija (2019) portrayed qualitative research as a constructivist paradigm informed by a subjective ontology. Qualitative research entangles the observer and subjects resulting in learning based on reflection and observation to create knowledge through the interpretation of meaning (Meunier, 2008; Ravitch & Carl, 2019). Although qualitative research is appropriate for many types of social inquiry, it was not the best choice for my research. I sought to determine whether fractal patterns of behaviors and attitudes aligned within SOFT, which required a mathematical expression of fractal behaviors and attitudes.

Mixed-Methods Research

Burkholder and Burbank (2019) described mixed-methods research as a fusion of quantitative and qualitative methods to extend the researcher's understanding of phenomena to help explain the science or behavioral aspects of practice or policy by integrating emic and etic perspectives. Mixed-methods research adds depth to quantitative approaches and objective rigor to qualitative approaches. Halcomb and Hickman (2015) proposed that mixed-methods research fills in the unknown blanks in independent quantitative and qualitative methodologies. Mixed-methods research is the best inquiry practice when the researcher seeks to explain unusual or unexpected results, or when qualitative methods are needed to explain the "why" of a question and quantitative methods are necessary to express the "what" or "how much" of a question (Halcomb, 2019). Because I sought to test the hypothesis of a measurable FD across organizational hierarchies and did not seek to understand unusual behavior, I did not include a qualitative component. Therefore, the study did not require a mixed-methods approach.

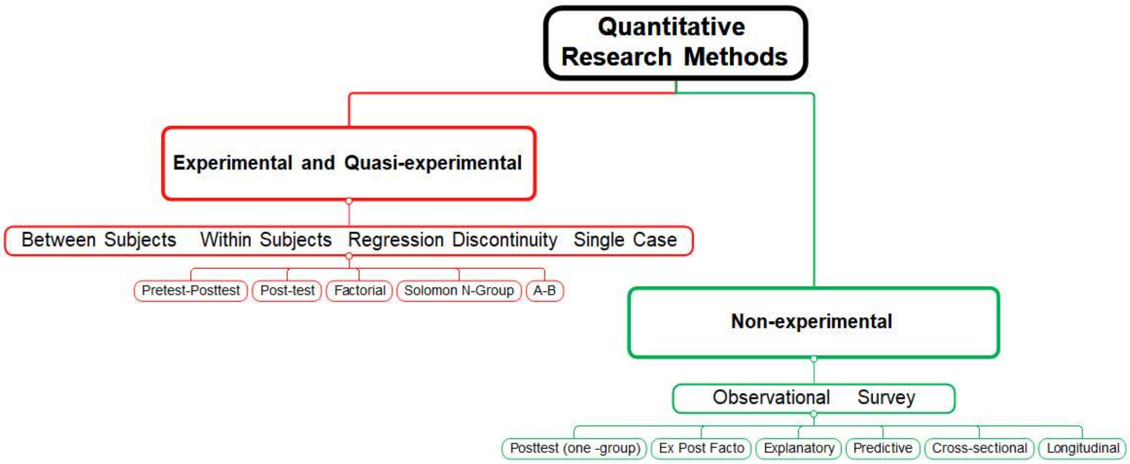
Selection of the Quantitative Research Design

Because a quantitative approach best suited my research intent, my next concern was which quantitative design to choose to best suit my inquiry. Edmonds and Kennedy (2017) classified the most common quantitative research designs based on experimental or nonexperimental methods. A graphical adaptation of Edmonds and Kennedy's quantitative design classification table is displayed in Figure 2.

Researchers using experimental and quasi-experimental designs control bias by randomizing the assignment of variables and controlling for differences between groups by considering the control groups used and counterbalancing the statistical power and measurement precision against Type I and Type II errors (Burkholder & Burbank, 2019; Pollatsek & Well, 1995; Sarkies et al., 2019). Reichardt (2009) characterized the differences between experimental and quasi-experimental designs by the researcher's ability to randomize samples or treatments. In quasi-experimental studies, there is a purposeful selection of samples or groups and the level of the application of the predictor variable. Both approaches require experimental controls to ensure proper sampling because of potential covariance (Trochim, n.d.) and nonequivalent group membership rules (Burkholder & Burbank, 2019).

Figure 2

Quantitative Research Methods and Designs



Note. Adapted From Edmonds and Kennedy (2017, pp. 117–118).

To execute an experimental or quasi-experimental design, I would have needed to compare the fractal dimensionality across the group participating in the changes and compare it to control groups who did not participate. I would have also needed to conduct the study with identical sets of operating conditions (see Kluge et al., 2019). This approach was impractical for my research because competitive engineering organizations such as aerospace firms tend to avoid formal organizational experimentation without prior evidence of its success (see Farooq et al., 2021).

Because my research goals were exploratory and had to be completed within a reasonable time frame, I pursued a nonexperimental approach to establish the credibility of my fractal emergence principle. Blalock (2018) characterized observational nonexperimental designs as those in which the independent or predictor variable is not manipulated. Price et al. (2012) advocated for nonexperimental research when the primary objectives of the study met four criteria:

1. The research goal is to understand a single variable instead of the relationship between variables.
2. The research is not intended to prove causality.
3. The predictor variable cannot be manipulated, nor can the participants be randomly assigned.
4. The study is broad or exploratory.

I was interested in exploring the nature of a single variable related to the degree of alignment across hierarchical boundaries. The predictor variable in my study was the FD computed for the degree of alignment between the responses from survey participants. Therefore, the first condition for nonexperimental design was met. Although there was a hint of causality implied in my research question, my goal was to examine whether fractal self-replication was present and was associated with OC success. My criterion variable was the degree of OC success reported by the participants. In a correlative design, bidirectionality prevents a causal interpretation of the association between criterion and predictor variables (Burkholder et al., 2016). My inquiry was correlative, not causal, satisfying the second criterion for a nonexperimental design. My FD measure of hierarchical alignment was an emergent property of the change process. I could not manipulate the predictor variable or randomly assign participants; therefore, the third criterion for a nonexperimental method was satisfied. Lastly, my research was broad and exploratory in nature. Therefore, all four conditions for conducting nonexperimental research were met.

Methodology

I chose a descriptive correlational design for my study because I sought to examine the relationship between two or more variables (see Curtis et al., 2016). Warner (2012) advised that a correlative analysis is appropriate for exploratory studies and confirmed that correlative or regressive techniques provide sufficient statistical strength to describe an association between factors and responses. To perform a correlational study, a researcher gathers representative data from a group to determine how changes to a predictor variable relate to changes in a criterion variable (Rumahlewang et al., 2021).

I utilized survey data to assess the research question for my correlative study. Burkholder et al. (2016) advocated for correlational designs when the experimental variables can be measured but cannot be manipulated to infer causality. I envisioned using a Pearson product-moment correlation to evaluate the relationship between predictor and criterion variables. My predictor variables were composite FD measures relating to creolization and resistive intent across organizational hierarchies. I calculated the fractal dimension value for each participant's survey response from the fractal dimension equations provided by Lumen Learning (n.d.), Shi (2013), and Yaffe and Boyd (2009). I assessed the criterion variable by calculating a mean value of the participants' ratings of OC success variables. I planned to use a Pearson correlational test to evaluate the relational association between fractal dimensionality and organizational change success. However, I also planned to assess associative strength using Kendall's tau and

Spearman's rho calculations as a contingency if the correlation results were nonparametric. Correlation studies are bidirectional, meaning that the test cannot determine if the association between the independent predictor and dependent criterion variables is causal (Burkholder et al., 2016). Therefore, the independent and dependent variables lose their cause-and-effect meaning and are commonly referred to as predictor and criterion variables. Because of the temporal relationship between alignment and OC success, the fractal dimension acted as the independent predictor variable. The participants' description of OC success was the dependent criterion variable. In the context of my research question, alignment precedes organizational change success, so it becomes the predictor variable in my quantitative, correlational, and nonexperimental study.

According to Edmonds and Kennedy (2017), the two most common options for non-experimental designs are observational and survey approaches. An observational approach was impractical for my research because of the lack of access to individuals within the aerospace community for direct observation. Security and proprietary concerns within the North American aerospace and defense business sectors make observational studies particularly challenging for researchers (see McCrie, 2016). However, Edmonds and Kennedy (2017) characterized survey method research as an efficient and effective method to understand the individual, team, and organizational characteristics within a social research setting.

The advantage of a survey approach for my study was that it did not require the direct control of the predictor or criterion variables. The survey method allowed me to assess the independent predictor variable and the dependent criterion variable concurrently or retrospectively (see Edmonds & Kennedy, 2017). Because my survey was intended for aerospace workers who had recently completed a formal OC project or were currently participating in an OC process, the survey method fit well into my nonexperimental correlative research plan. My research instrument was an online, self-administered survey to provide the responses needed for my study. I will discuss the population, sampling procedures, and data collection process in the next sections.

Target Population

The population for my study comprised current or former North American aerospace employees who had recently completed or were completing a largescale organizational change. The estimated population of aerospace workers at the time of my study was 509,000 in the United States (USA.gov, 2018). There were approximately 89,000 aerospace employees in Canada (Canadian Council for Aviation & Aerospace, 2018), and 28,807 in Mexico (López, 2021). Therefore, the total population of aerospace workers was approximately 626,807 for North America. My study sample constituted self-selected employees from North American aerospace organizations contacted through open invitation in social media sites.

Self-selection sampling is a nonprobability sampling practice that allows individuals to choose whether to participate in a study. The primary advantage of using a self-selection process for my study is that it afforded a greater level of commitment from survey participants because it was their choice to participate (see Lehdonvirta et al., 2021). Another advantage of a self-selection sampling process to recruit people for my study from North American aerospace companies was that it minimized the time required to find individuals who meet the employment selection criteria (see Keiding & Louis, 2018).

Self-selection sampling was appropriate for my investigation because I required that participants had work experience in North American aerospace companies but there was no verified list of aerospace workers generally available. Therefore, a truly random sampling of the aerospace population was not possible. The primary weakness of self-selection sampling in my study was that it introduced the potential for self-selection bias. I discuss self-selection bias in the consideration of threats to validity section of this chapter. However, I mitigated some of the risks of selection bias by including several different social media sites like Linkedin, Walden participant pool, Facebook, and SurveyCircle.

Sampling and Sampling Procedures

Because I conducted a correlative study, the sample size required to fairly represent the North American aerospace community had to contain a sufficient sample size to assess the Pearson product moment correlation coefficient. The Pearson correlation coefficient is a dimensionless indicator of the relationship between a predictor and a criterion variable. The Pearson correlation provides a value from -1 to 1, depending on the linear relationship between the predictor and criterion values (Warner, 2012). A negative value indicates a negative relationship, meaning as the predictor variable increases, the criterion variable decreases. A positive coefficient value indicates a positive correlation, meaning that as the predictor variable increases, the criterion value increases. A Pearson product moment correlation coefficient of 0 indicates no discernable relationship at the confidence level determined for the analysis. Because my research design was correlative, I was careful to select an appropriate minimum sample size. If the sample size was too small, the reliability of the Pearson correlation coefficient would be low and might have misrepresented the true association between the predictor and criterion variables (see Sari et al., 2017).

My sample size estimate depended on how I planned to assess the data to answer my research questions. I considered the sample size three ways. The first was to determine how many participants were needed to represent the North American aerospace population. I calculated the sample size for the estimation of a proportion in a finite population using the method described by Karim et al. (2019) and Del Águila and González-Ramírez (2014):

$$n_{min} = \frac{t_{\alpha}^{2} * p * (1-p) * N}{(N-1) * e^{2} + t_{\alpha}^{2} * p * (1-p)} \quad (6)$$

Where n_{min} = the minimum sample required; N = the size of the target population from which the sample was drawn; p = expected percentage of the response variable; e = accepted margin of error; and t_{α} = the value of the normal curve associated with the confidence interval. The value for t_{α} was 1.96 for a confidence of 95% (Del Águila & González-Ramírez, 2014). Because I did not know the variability in the proportion, I conservatively set it to its maximum variability at p = 0.5 (Israel, 2009). Because my study was exploratory and I was attempting to provide proof-of-concept, I reasoned that I could accept a result within 10% of the observed value. Therefore, my value for the expected margin of error was 0.10. A 10% margin of error is similar to the sampling strategy employed by Wong et al. (2021) to explore novel cancer treatment techniques.

Given that $t_\alpha = 1.96$ ($\alpha = 95\%$), N = 626,806, p=0.5, and e = 0.10, the calculated sample size for the North American aerospace community was:

$$n_{min} = 96 \text{ survey participants}$$

I elected to use a 95% level of confidence for the sample size calculation. McLeod (2019) advised that the use of a 95% confidence is prudent in sample size calculations because it indicates that one can be 95% confident that the confidence intervals from responses of the sampled population contain the true response from the whole population. A 95% confidence level indicated a 5% chance of accepting the alternative hypothesis if the null hypothesis was actually true. This is also referred to as the alpha risk (α) of making a Type I error. A Type II (β risk) error occurs when a researcher fails to reject the null hypothesis when it is false. Another way of stating the use of a 95% confidence in the sample size is that it provided a 95% chance that I would not make an error in generalizing the study from the sampled population by applying it to the entire population (Rea & Parker, 2014).

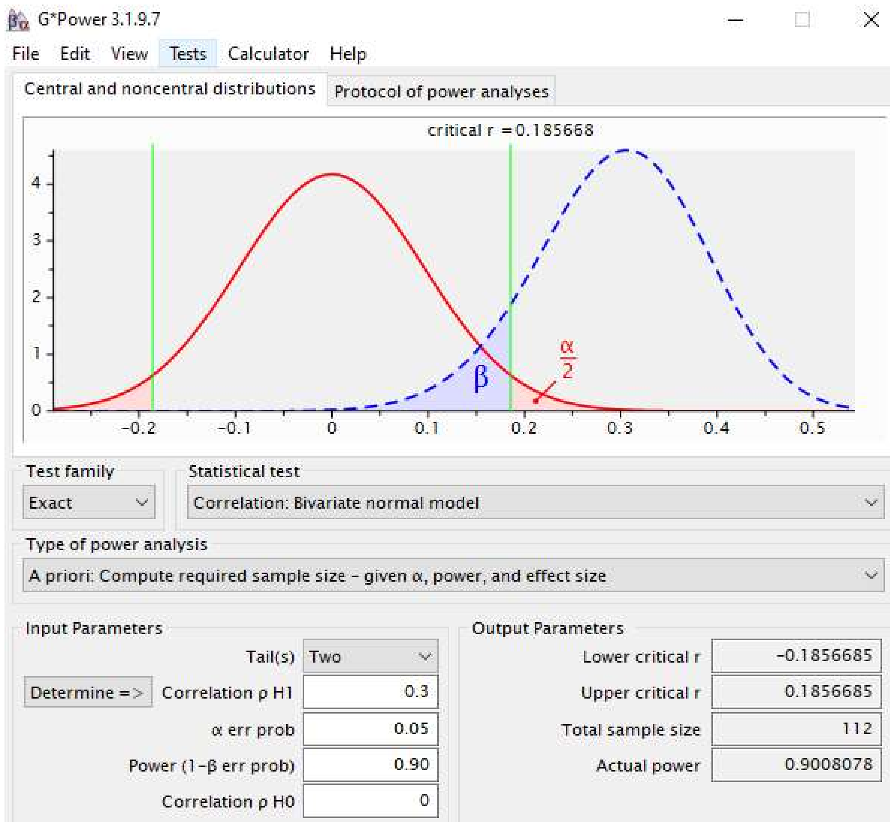
Using Equation 6, I calculated that I required at least 96 participants to create a statistically representative study of North American aerospace workers. However, because I was also analyzing the fractal dimension across hierarchical levels using creolization and resistive intent themes, I needed to evaluate my sample size from the perspective of finding themes within the data. Given that my research inquiry utilized a survey based on creolization and resistance to change themes across organizational boundaries, I also evaluated my sample size strategy for its ability to resolve themes in survey data, as recommended by Fugard and Potts (2015). My study included thematic interpretations of creolization with four constituent subthemes and resistance to change with six constituent subthemes. Therefore, I required a study population capable of identifying 10 total themes across three levels of hierarchy for a sum product of 30 themes. Given the reported ~20% success rate for change initiatives (Jones-Schenk, 2019), I needed to ensure that my sample size was greater than the ability to discern 30 themes from the 80% power table provided by Fugard and Potts. Therefore, I required at least 113 samples from the thematic prevalence table to ensure an 80% power of finding distinct thematic differences. I calculated the margin of error for a sample size of 113 using Minitab and found that my thematic sample estimate provided a 0.31 Likert-unit margin of error for the correlative determination of fractal dimension at a 95% confidence.

In the first two sample size estimates, I considered the sample sizes needed to assess the representativeness of the North American aerospace population given a thematic study. Although the first two methods assured the minimum sample sizes necessary to represent the aerospace industry and find research themes, I also needed to determine the appropriate sample size for a correlative test of fractal dimension and OC success. The Pearson product moment correlation is a type of bivariate normal mode study. A bivariate normal model correlation study was appropriate for my inquiry because the method allowed me to assess large datasets with mixed-type attributes (Daru et al., 2021). I selected a two-tail analysis to evaluate whether there was a positive or negative correlation between dimensionality and success. A two-tailed analysis was appropriate because it included the possibility that fractal dimensionality was negatively associated with OC success. I chose an a priori analysis of the sample size given a medium Cohen's effect size of 0.3 (see Duesbery & Twyman, 2020), an alpha risk of 5%, and a relatively large power value of 0.9. I selected the 90% power value at a slightly higher value than the conventional 80% power used in most exploratory research because I wanted to ensure that I had a high probability of observing the association between FD on OC success in the study if there was a true effect present to detect (see Azam et al., 2021). Using G*Power software (Faul et al., 2009), I calculated the minimum sample size for a bivariate correlation study given the aforementioned parameters. Based on the G*Power analysis shown in Figure 3, I determined that my minimum sample size for a bivariate correlation study was 112.

My consideration of the three methods used to determine the sample size to represent the North American aerospace workforce and address my research design resulted in a minimum sample size range from 96 to 113. I chose the most conservative interpretation by selecting the largest of the three sample size estimates. Therefore, I concluded that I required at least 113 valid participant responses.

Figure 3

*Determination of Sample Size Needed for A Priori Analysis of the Research Question Using G*Power*



Procedures for Recruitment, Participation, and Data Collection

I collected primary data for this study using the online survey website SurveyMonkey. I used SurveyMonkey to administer the survey because the service provided faster and more cost-effective data collection and responses than was possible using paper surveys. The SurveyMonkey tool allowed me to create individual hyperlinks for each social media site I used to solicit volunteers. By tracking individual hyperlink traffic, I was able to determine which social media site contacts provided the most responses. I then used social media contact sites like Linkedin, Facebook, and SurveyCircle to invite participants using the “splash page” included in Appendix F. Volunteer candidate participants were directed to the SurveyMonkey hyperlink. The first page of the survey screened the candidate for implied consent confirmation and verified that the participant satisfied my pre-selection criteria. The pre-selection criteria for self-selective participation in my study included a verification that the candidate was at least 18 years old and confirmation that the participant is or was a current or former North American aerospace worker. A third preselection requirement was that the candidate has participated in an organizational change event or process while employed as an aerospace worker. The screening questions were not stored as part of the survey answers and were only used for the participants to gain access the survey.

If the participant passed the screening question, the survey tool directed the candidate to the informed consent screen. The informed consent process is described in the next section. An advantage of a service like SurveyMonkey was its ability to store the survey data on a protected and encrypted database during the data collection phase while still allowing me to export the digital data into Minitab and Excel.

During the data collection phase of my study, I monitored the participant demographics to ensure that the volunteers appeared to represent the published demographics of the North American Aerospace workers population. My research plan included provisions to keep the survey open longer than its planned 31 day duration if I was not getting a good representation of member demographics. However, by visiting the social media sites and resubmitting my recruitment splash page to invite participants on a near-daily basis, I was able to acquire a sufficient sample size and demographic distribution within the 31-day plan.

Once admitted to the survey, the participants were asked ten demographic questions that became part of the survey response dataset:

1. DI0 -Are you a current of former aerospace employee? (Y/N)
2. DI1 – What is your current age?
3. DI2 – Which of the following best describes you? (Please select the best answer): Asian or Pacific Islander; Black or African American; Hispanic or Latino; Native American or Alaskan Native; White or Caucasian; Multiracial or Biracial; A race or ethnicity not listed here; I prefer not to answer.)
4. DI3 - What gender do you identify as? (M/F/other/prefer not to answer)
5. DI4 - Number of years you worked in the organization?
6. DI5 - Approximately how many employees are in your organization?
7. DI6 - Your Level in the organization at the time of the change initiative (choose one): 1= Worker/professional, 2 = Manager, 3 = Executive
8. DI7- How long did the change take to complete, or how long is it expected to take from the time it started until it is completed (in months)?
9. DI8 - Your estimate for the percentage complete of the change process?
10. DI9 - Number of months since the organizational change was completed?

The demographic information DI0, DI1, DI2, DI3, and DI4 were used to ensure that the volunteers represented the published aerospace demographic breakdown.

Questions DI5-DI9 were used to pivot the analysis for different themes. Question DI6 was used to place the participants' responses into the right hierarchical level to calculate fractal dimensionality. Question DI8 was used to screen out participants who have not yet participated in OC. I removed the survey results from any participant who had not completed at least 25% of the survey at the end of the 31-day data collection window.

During the survey and up to submitting the final response, the participants could refuse to answer a question or elect to opt-out of participation altogether. I provided explicit anonymity assurances to the participants in advance of their participation. I considered the option to refuse to answer or continue to participate a fundamental right of the survey participant. Bentley et al. (2020) found that many survey respondents skipped or failed to complete surveys that do not resonate with their perceived best interests. For example, a participant might have worried that the study was too personally identifiable or posed a risk of harmful exposure to themselves or their company.

Once the applicant was granted access to the survey through their confirmation of informed consent, they were presented with the survey itself. The survey contained 34 Likert-type scale questions ranging from 0-10. It also included two ordinal and two nominal questions regarding the participants' assessment of the change program's success. The survey also incorporated nine demographic questions. The specific questions and their level of measurement are included in Appendix A.

If a participant opted out of the survey any time prior to their final review and submission, their responses and corresponding demographic information was omitted from the dataset. Upon completion of their survey, the participants were given another opportunity to review and change their responses. Once they were satisfied with their survey responses, the participants were given an opportunity to select a “submit” button to close the survey. After the survey was completed, participants were directed to a debriefing web page that thanked them for their participation. All participants were given a link to where a copy of the final report would be published to refer to the study if desired. Before exiting the survey, the participants were given one last chance to remove their submission from the dataset and opt out of the survey. Participants had 21 days to complete the survey or until the polling closed on the 31st day, whichever came first.

Informed Consent

After participants selected the link provided in the survey invitation letter, they were directed to the online SurveyMonkey platform. The first page of the survey contained a letter of implied consent that volunteers were required to complete before being granted access to the study. The informed consent screen was fully reviewed and approved by the Walden independent review board prior to its use or the collection of any data. The implied consent form described the research project, its goals, the length of the survey, and a brief explanation of what was expected from the participant. The consent statement also informed the candidate of their rights of refusal and described how their identity and anonymity would be protected. The consent form advised the participant that they had the right to skip any question they did not feel comfortable answering. The participants were informed that they had the right to review and edit their responses before the final submission. The implied consent form also included information on who to contact if participants had any concerns about their treatment or experience during their participation. I mandated that the candidates acknowledge their consent by incorporating a checkbox for the candidate to click to affirm that they understood and agreed to participate and confirm that they were at least 18 years old.

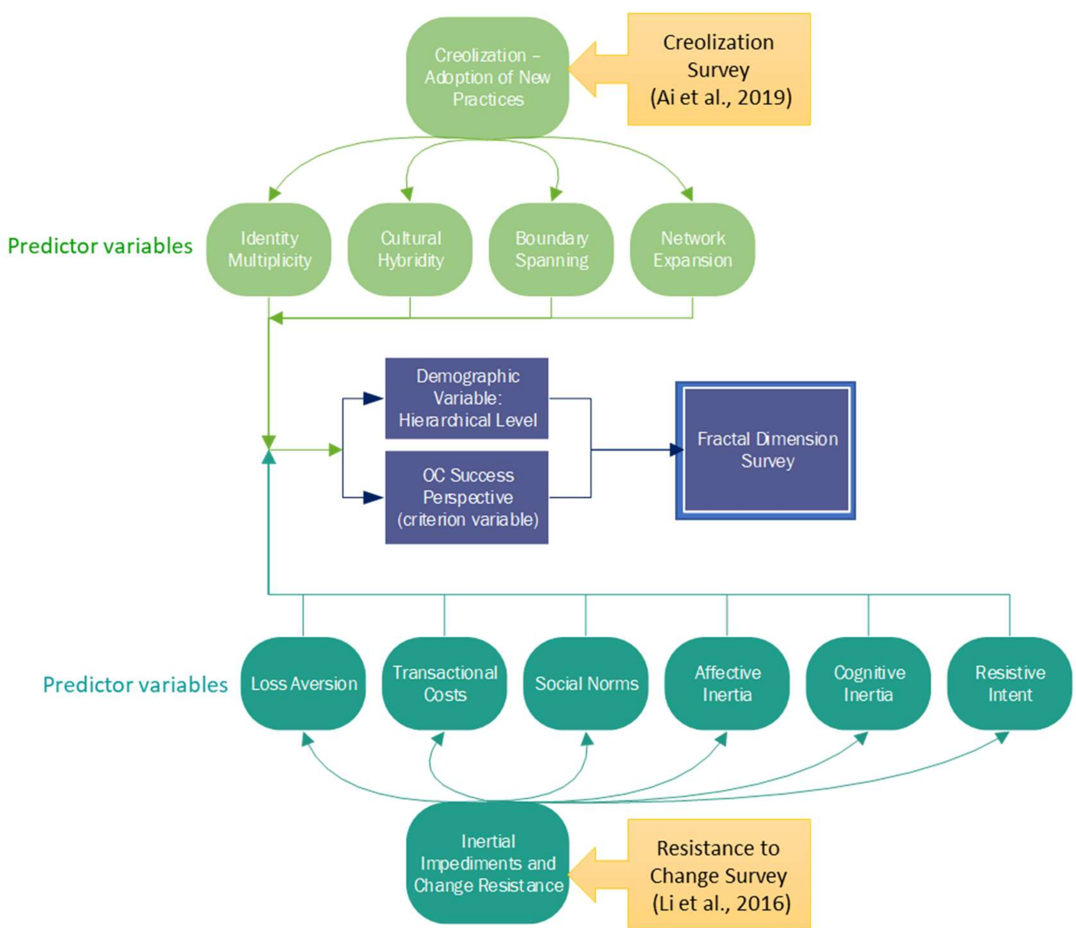
Instrumentation and Operationalization of Constructs

According to McDonald (2021), survey research is the most common form of quantitative social research. One possible reason for surveys' popularity is their efficiency. Surveys can acquire large amounts of data for a large population within a relatively short timeframe. I utilized a synthesis of two previously validated survey instruments to gather data for my investigation. For this study, I combined a survey relating to the adoption of new cultures (creolization) and a study intended to measure change resistance by Ai et al. (2019) and Li et al. (2016), respectively.

The creolization survey developed by Ai et al. (2019) was designed to gauge how partnering firms managed change in cross-cultural processes. As shown in Figure 4, Ai et al.'s instrument characterized how behavior and attitudes changed during a transformation by measuring identity multiplicity, cultural hybridity, boundary spanning, and network expansion. In the context of organizational change, identity multiplicity refers to adopting new social traits through the adoption of new social norms (Abbott et al., 2013). Cultural hybridity describes the emergence of a cultural synthesis that blends current practices with desired practices, providing evidence of change and internalizing new behaviors (Ai et al., 2019; Cockcroft, 2019). Boundary spanning facilitates organizational change through interaction across social domain borders (Ai et al., 2019) and refers to communicating across administrative and hierarchical boundaries (Giorgio et al., 2020). Ai et al. (2019) described network expansion as "the generation and formation of connections between disparate national networks of partnerships between organizations" (p. 20). The Ai et al. (2019) survey consisted of 14 questions, each assessed using a 5-point Likert-type scale. The authors did not mention how long their survey took to complete. I obtained permission to use the instrument from the publisher and included a copy of the authorization for use in Appendix A.

Figure 4

Fractal Dimension Survey Elements



Li et al. (2016) studied resistance to change and developed their survey to study how workers in a large Chinese petrochemical plant adopted a new knowledge management system. The resistance to change instrument measured how individual behaviors and behavioral intents contributed to an individual's resistance to change. As shown in Figure 4, Li et al.'s survey contained 16 questions related to the inertial aspects of resistive intent: (1) loss aversion; (2) transactional costs; (3) social norms; (4) affective inertia; (5) cognitive inertia; and (6) resistive intent. Loss aversion describes how the respondent felt regarding their previous way of behaving or operating and if they perceived a perceived benefit from the established patterns of behavior that might prevent them from using the preferred or new pattern of behavior (Ryan, 2016). Transactional costs refer to the respondent's perceptions about the difficulty in learning the new way of working and the overall effort required to operate within the OC paradigm (Kim & Kankanhalli, 2009; Li et al., 2016). Social norms measured the respondent's perspective of how their peers, managers, and subordinates felt about the change and characterized individuals' beliefs and behaviors as a part of a socially accepted norm (Janmaimool, 2017). Affective inertia assessed the respondent's mood regarding the change based on a perception that the old pattern of behavior was more comfortable or less stressful than the new way of working (König et al., 2021; Li et al., 2016). Like affective inertia, cognitive inertia described the respondent's conscious intent to continue working in the pre-change mode of behavior. Lastly, resistive intent captured the degree to which the person chose to resist the organizational change and opposed the performing the new, desired pattern of behaviors. I obtained permission to use the instrument from the publisher and included a copy of the authorization for use in Appendix B.

Both surveys were required for my study because a fractal view of organizational alignment relates to both behaviors and beliefs. Figure 4 depicts how I envisioned the synthesis of both surveys to assess fractal dimensionality. The Ai et al. (2019) instrument addressed creolization and was appropriate for gauging the dispersion of the participants' attitudes and beliefs from pre-change through change adoption. However, the Ai et al. tool in isolation does not measure the inertial and behavioral aspects of change. Therefore, I included the Li et al. (2016) survey to capture the participants' behaviors and attitudes toward change. The Li et al. survey helped reveal how attitudinal inertia affected the participants' ability to accept and comply with the change objectives. Li et al. described their instrument as being particularly adept at characterizing differences in resistance to change across organizational hierarchy levels. A combination of the two surveys with the participant's reported level in the organization allowed me to calculate the fractal dimension for hierarchical alignment.

Both survey tool authors worded their original instruments to address their specific study demographic and workplace settings. Ai et al.'s (2019) survey was designed to look at OC transformations across an information technology project spanning two countries, while Li et al. (2016) phrased their survey to accommodate Chinese workers and knowledge management systems. Accordingly, I carefully rephrased the wording of the original survey to suit a North American aerospace community in the context of generalized change. This rephrasing did not substantively change the questions' impact nor their intent. A comparison of the original survey questions and the adjusted questions is provided in Appendix A. Neither the Ai et al. nor the Li et al. surveys mentioned the expected length of time required to complete their survey. However, I anticipated the survey, which I named "the fractal emergence survey" would take approximately 30 minutes to complete.

The fractal dimension calculation required information about the respondents' organizational level at the time of the change and compared it to the participants' perceptions of how workers, managers, and executives also performed during the change process. I also needed the participants' assessment of the success of the OC outcome to calculate the criterion variable for OC success. Therefore, in addition to the creolization and change resistance questions, I added demographic and change success measures to the hybridized survey. I also collected demographic information (DI) as part of the survey dataset. Although I did not collect any personally identifying information about the participants, I used the demographic data to infer hierarchical levels within the organization in case I needed to control for demographic differences between my sample population and the published demographics for North American aerospace workers.

I operationalized three types of variables for this study: predictor variables related to the resistance to change and creolization of beliefs, criterion variables related to the participants' assessments of the success of the change, and demographic variable used to indicate the participants' roles in the organization for use in calculating fractal dimension. Table 1 contains a variables table list of the survey questions and their measurement type. According to Santucci (2021), there are four basic levels of variable measurement: (a) nominal, (b) ordinal, (c) interval, and (d) ratio. Nominal values represent categories or groups and can be coded or categorical. The fractal emergence instrument contains each of these variable levels.

The fractal emergence survey utilized three nominal variables. Question DI0 asked if the participant is a current or was a former aerospace employee. Question DI2 assessed the gender of the participant. And question CS4 asked a yes/no question regarding organizational success to help assess the OC success criterion variable.

Like nominal scales, ordinal scales also measure categories, however nominal scales reflect a degree of measurement associated with a ranking. Likert-type scales fall into the category of ordinal variables; however, they are commonly treated like interval variables in survey analyses (Wu & Leung, 2017). Survey questions IM1-5, CH1-3, BS1-4, NE1-3, LA1-2, TC1-5, SN1-3, AF1-3, CI1-3, and RI1-4 established my predictor variables, and were all ordinal scale variables. Questions CS1-3 were also ordinal scale variable; however, these variables were statements relating to the success of the OC and were used to determine the criterion variable. I assessed each variable using an 11-point Likert-type agreement scale (0-10), where a value of 0 indicated no agreement at all and a value of 10 meant that the respondent completely agreed. Wu and Leung (2017) advised that using a 10-point agreement scale allowed for a sufficient range of measures and enabled the researcher to compute a statistically relevant value for the variable distribution, mean, and standard deviation of survey responses when given sufficient sample size. Although my predictor variables were ordinal, I analyzed them as quasi-interval values.

Table 1

Variables Table Showing Level of Measure for Each Survey Variable

Variables table for the Fractal Emergence Survey

Dimension or Category	Variable Name	Reversed Coded?	Survey Question	Level of Measurement	Measure
Identity Multiplicity (IM)	IM1	No	IM1 - In general Managers and workers share similar values in this company	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	IM2	No	IM2 - I believe that my manager's commitment to the change initiative and mine (are/were) similar.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	IM3	No	IM3 - Managers and employees in this company tend to interact on an equal basis.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	IM4	No	IM4 - I think the goal of the change my company envisioned (moves/moved) us closer to our core values and who we want to be as a company.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Cultural Hybridity	CH1	No	CH1 - In project teams, we (have changed or have started to change) our organizational practices because of the change initiative.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	CH2	No	CH2 - I believe my colleagues and I (have changed or are very likely to change) the way we work to align with the goals of the change initiative	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	CH3	No	CH3 - In my day-to-day work, I have changed the way I (behave/behaved) as a result of the change initiative.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Boundary Spanning	BS1	No	BS1 - My immediate manager and I (discuss/discussed) how to best implement change.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	BS2	No	BS2 - One or more of my colleagues or coworkers routinely (discuss/discussed) the change initiative.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	BS3	No	BS3 - One or more of my peers or colleagues (has been/was) formally or informally designated to help my group reach its goals with respect to the desired change.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	BS4	No	BS4 - One or more members of our senior management team (have/had) training in the change process or (has/had) experience implementing this kind of change.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Network Expansion	NE1	No	NE1 - I believe that our senior management (considered/considers) the change worth the effort and (believes/believed) that the change will improve the company performance in the long run.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	NE2	No	NE2 - One or more members of the senior management team (was/are) capable of helping me achieve the goals of the change initiative.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	NE3	No	NE3 - I think that other groups within my company (adopted/are adopting) the change well.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)

Table1 (continued)

Variables table for the Fractal Emergence Survey

Dimension or Category	Variable Name	Reversed Coded?	Survey Question	Level of Measurement	Measure
Loss Aversion	LA1	Yes	LA1 - Before the change, my previous way of working gave advantages or privileges that I (did not / would not) receive compared to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	LA2	Yes	LA2 - Before the change, my previous way of working was more effective and (was/would be) reduced if I were to switch to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Transaction Costs	TC1	Yes	TC1 - It (did/would) take a lot of time and effort to switch to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	TC2	Yes	TC2 - I (did/would) lose a lot in my work if I were to switch to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	TC3	Yes	TC3 - Switching to the new way of working (did/could) result in unexpected hassles.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	TC4	Yes	TC4 - Learning what I need to do differently to be aligned with the goals of the change (did/would) take much time or (was not/might not be) worth the effort.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	TC5	Yes	TC5 - Becoming skillful at using the new processes (was not/would not be) easy for me or my teammates.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Social Norms	SN1	No	SN1 - My colleagues think I should use the new/changed process. [reverse-coded item]	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	SN2	No	SN2 - My managers think I should use the new/changed process. [reverse-coded item]	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	SN3	No	SN3 - My subordinates think I should use the new/changed process [reverse-coded item]	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Affective Inertia	AF1	Yes	AF1 -I plan on using my pre-change method for getting work done or working with my teammates…because it would be stressful to change.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	AF2	Yes	AF2 - I plan on using my pre-change method for getting work done or working with my teammates…because I am comfortable doing so.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
	AF3	Yes	AF3 - I plan on using my pre-change method for getting work done or working with my teammates…because I enjoy doing so.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)

Table 1 (continued)

Variables Table for the Fractal Dimension Survey

Source	Dimension or Category	Variable Name	Survey Question	Level of Measurement	Measure
Li et al. (2016)	Cognitive Inertia	CI1	CI1 - I plan on using my pre-change method for getting work done or working with my subordinates…even though I know it is not the best way of doing things.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		CI2	CI2 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most efficient way of doing things	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		CI3	CI3 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most effective way to do things.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Li et al. (2016)	Resistive Intention	RI1	RI1 - I fully support/supported the change to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		RI2	RI2 - I will fully cooperate/cooperated with the change to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		RI3	RI3 - I intended/intend to comply with the change to the new way of working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		RI4	RI4 – I (did not /do not) think the change initiative is needed.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
Change Success		CS1	CS1 - I (did not /do not) think the initiative worked or is currently working.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		CS2	CS2 - I (did not /do not) think the initiative (was/will be) successful.	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		CS3	CS3 – Reflecting on the change process, based on what you know of what was expected of the outcome, do you think the change was successful?	Ordinal, but analyzed as interval	11 point Likert-Like scale (0-10 level of agreement)
		CS4	CS4 - Do you believe that the change process met its goals?	Nominal	Binary Y/N coded as Boolean 1/0

Table 1 (continued)

Variables table for the Fractal Emergence Survey

Dimension or Category	Variable Name	Reversed Coded?	Survey Question	Level of Measurement	Measure
Demographic Information	DI0	No	DI0-Are you a current or former aerospace employee (Y/N)?	Nominal	Binary Y/N stored as coded 1/0
	DI1	No	DI1 - What is your Age in years?	Ratio	Continuous data, yrs.
	DI2	No	DI2 - Which of the following best describes you? Please select the best answer: Asian or Pacific Islander, Black or African American, Hispanic or Latino, Native American or Alaskan Native, White or Caucasian, Multiracial or Biracial, A race or ethnicity not listed here, I prefer not to answer.	Nominal	Discrete, categorical text, coded 1-9
	DI3	No	DI3-What gender do you identify as? (M/F/other/prefer not to answer)	Nominal	Discrete, categorical text, coded 1-4
	DI5	No	DI4 - Number of years you have worked in this organization	Ratio	Discrete integer data (yrs.) but treated as continuous
	DI4	No	DI5 - Approximately how many employees are in your organization?	Ratio	Discrete integer data (counts) but treated as continuous
	DI6	No	DI6 - Your Level in the organization at the time of the change initiative (circle one): Worker, Manager, Senior Manager, Executive Manager	Ordinal	Discreet, categorical coded 1/2/3
	DI7	No	DI7 - How long did the change take to complete, or how long is it expected to take from the time it started until it is completed (in months)? ____________	Ratio	Discrete integer data (months) but treated as continuous
	DI8	No	DI8 - Your estimate for the percentage complete the change process is (0-100%)	Interval	Proportion based on degree of completion
	DI9	No	DI9 - Number of months since the organizational change was completed (0=still ongoing,)	Ratio	Discrete integer data (yrs.) but treated as continuous

Interval scale measures are like ordinal scale measures except that the distance between consecutive numbers on the scale is equal. Question DI7 was an interval scale measure. I asked the participant to estimate the percentage completed for the organizational change process, with 0% indicating that there had been no progress on completing the change and a 100% suggesting that the process was complete. I used the D17 variable to identify participants who had not started the change process.

Ratio scale measures contain values that are absolute and have an absolute zero point that reflects the absence of a measurement (Santucci, 2021). The fractal emergence survey contained 5 ratio scale measures. Question (DI1) assessed the age of the participant for comparison to published aerospace demographics. Question DI4 described the number of years the participant had worked with the company up to the time of the OC project. Question DI5 asked the participant to estimate the number of employees in the organization at the time of the change. Question DI7 asked the participant to estimate the length of time for change to complete. And question DI6, and number of months since the change had completed.

Both of the surveys used to construct the fractal emergence survey instrument were validated by their originators to confirm the internal consistency and reliability of their constructs relating to OC success.

Li et al. (2016) assessed the reliability and convergent validity of the seven constructs used in their resistance to change survey using CFA.

- Loss aversion (Cronbach Alpha = 0.871),
- Transactional costs (Cronbach Alpha = 0.896),

- Social norms (Cronbach Alpha = 0.887),
- Affective inertia (Cronbach Alpha = 0.840),
- Behavioral inertia (Cronbach Alpha = 0.888),
- Cognitive inertia (Cronbach Alpha = 0.969),
- Resistive intent (Cronbach Alpha = 0.940).

The authors reported that the composite reliability of each score exceeded 0.9 for all variables.

Ai et al. (2019) verified the construct validity of their instrument using partial least squares (PLS) to assess the formative weights in the measurement model. The authors verified the bivariate item-to-construct correlation for each of their constructs:

- Identity multiplicity ($r>0.3$, $p< 0.01$ for all factors),
- Cultural hybridity ($r>0.4$, $p< 0.01$ for all factors),
- Boundary spanning ($r>0.3$, $p< 0.01$ for all factors),
- Network expansion ($r>0.3$, $p< 0.01$ for all factors).

Ai et al. (2019) also verified the convergent and discriminant validity of their instrument by examining the inter-item and item-to-construct correlations, per the method described by Loch et al. (2003). Each of the constructs relative to the degree of creolization success was significant to a 99% confidence. Because I used previously validated surveys, I did not perform a pilot study of the fractal emergence survey and instead confirmed validity using CFA and factor analysis to affirm the validity of my constructs.

Data Analysis Plan

Data Cleaning and Screening

I collected data for 31 days, after which I reviewed the demographic participation of the survey. Based on percentages, I analyzed the demographic data and compared it to data published by American Institute of Aeronautics and Astronautics (AIAA) for North American aerospace companies for gender, age, and race. Although there were no significant discrepancies (larger than 20%) in the participation in my survey compared to the demographics reported by AIAA, I left the survey open for an additional ten days to ensure that I had provided sufficient time to reach as diverse a population as possible. After 31 days, I had adequate volunteer participation and was within my demographic goal to have a response demographic within 20% of the AIAA percentages overall. I assessed the data from the fractal dimension survey using Minitab (minitab.com), V20, Microsoft Excel, and SPSS.

After I was satisfied that my demographic values fairly represented the North American aerospace population, I reviewed the dataset for missing data. In my original design, I had planned to address missing and nonresponse data by replacing it with values created using multiple imputation, as described by Lang and Little (2018). The multiple imputation method helps overcome mean substitution biases (Brick & Kalton, 1996) and was applicable for missing predictor, criterion, or demographic variables (see Lang & Little, 2018). However, multiple imputation was not needed because I had a sufficiently large sample of complete forms, as I describe in Chapter 4.

After addressing missing and nonresponse data, I ran descriptive statistics for each predictor and criterion variable, including mean, standard deviation, range, skewness, kurtosis, and the Anderson-Darling normality test. The descriptive statistics helped me identify any outliers or transcription errors in the data. I ran a confirmatory factor analysis and item analysis (IA) of the themes used within the survey to ensure that my repurposing of the two surveys had not altered their reliability. The CFA and IA also helped identify the covariance in my model.

Following the CFA, I exported the survey responses to Microsoft Excel to calculate the fractal dimension for each participant. The details of the fractal dimension calculation and the resulting correlation test follow.

Calculating the Fractal Dimension

In fractal geometry, *dimension* relates to the number of individual planes needed to describe a shape. For example, a dimension of 1 indicates a line, a dimension of 2 indicates a flat shape, and a 3-dimensional shape represents a shape like a cube, cylinder, or pyramid. The *scale* indicates the number of smaller copies that are promulgated across each dimensional axis. To scale a D-dimensional shape by a scaling factor S, the number of copies of the original shape needed can be expressed by (Lumen Learning, n.d.; Shi, 2013):

$\text{Copies} = \text{Scale}^{\text{Dimension}}$, (1)

Rearranging this equation and solving for dimension:

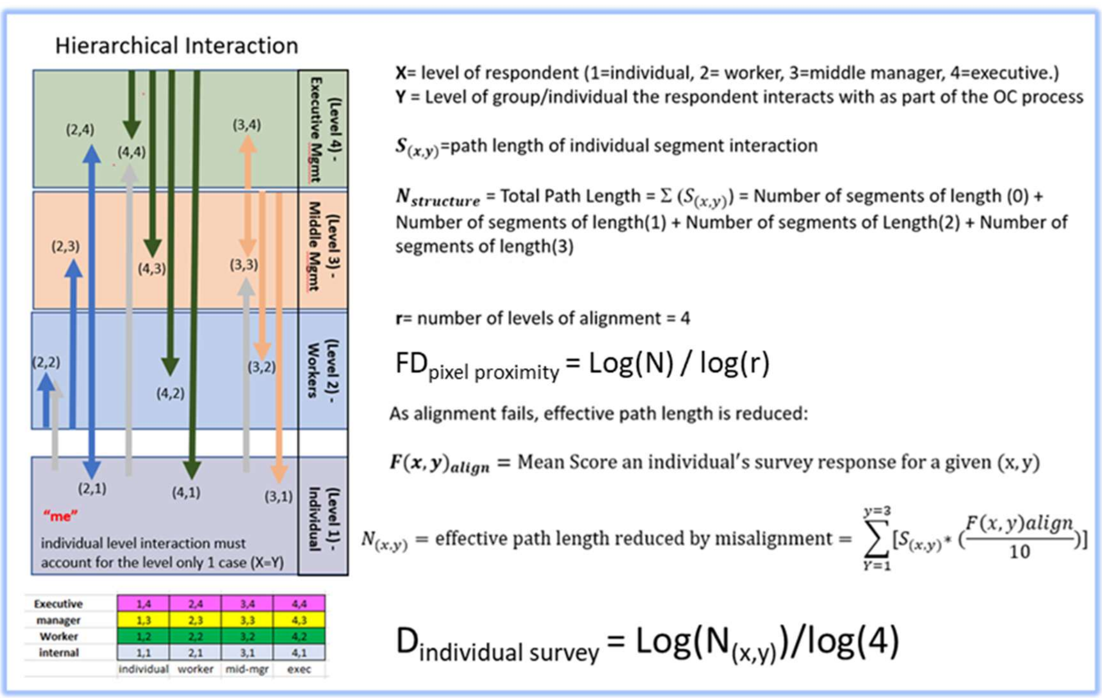
$\text{Log(Copies)} = \text{Dimension*log(Scale)}$; (2)

$FD_{\text{Replication}} = \text{Dimension} = \text{log(Copies)/ log(Scale)}$ (3)

For my study, the scale value represented the number of organizational levels that are relevant to the change. For example, if I consider workers at the first level, middle managers at the second level, and executive managers at the third level, the scale number would be 2, indicating the number of levels between executives and workers. However, in a survey where an individual reports their interactions within a peer group, the scale value is increased to 4 to include the individual in relation to their peer group and the interaction between peer groups. A visualization of how the fractal dimensions were determined by organizational level is depicted in Figure 5.

Figure 5

Conceptualization of Dimensionality Calculations Based on Scale and Path Length of Interaction Between Hierarchical Levels



Equation 3 is a relatively simple measure of fractal dimensionality based on replication. However, because my investigation was exploratory, I also calculated fractal dimensionality by pixel proximity, similar to how fractal dimensions are used to screen for cancer in radiography. Yaffe and Boyd (2009) studied fractal image analysis to detect breast cancer risk using mammography images. The authors found that highly complex pixel analysis could be shortened significantly using fractal dimensionality. The authors contrasted the image intensity of nearby pixels on a mammography image to assess the degree of fractal self-similarity as a function of distance from the pixel of interest. They based their study on Brownian motion techniques used to measure image textures as described by Lundahl et al. (1986). At the time of the Lundahl et al.'s study publication, many image experts concluded that image analysis for breast cancer screening was too complicated to allow for real-time analysis of mammogram images. However, Yaffe and Boyd (2009) simplified the process by looking for the linearity of brightness levels across neighboring pixels in the photograph. Yaffe and Boyd determined the brightness of each pixel at a given cartesian coordinate (x, y) in a digitized image. By assessing the two-dimensional structure of pixels of given scales (sized $\varepsilon \times \varepsilon$), the authors could resolve a comparative surface like that shown in Figure 6(a).

The determination of similarity between different pixels is found by first looking at given areas, $A(\varepsilon)$, where values are similar for a given image pixel size, ε. Yaffe and Boyd (2009) found that the surface area could be determined by the summation of the area of each pixel, ε^2, and the contributions of neighboring "exposed" sides of pixel area boxes. The expression of similar areas, therefore, is expressed by differences between neighboring pixel areas of illumination intensity:

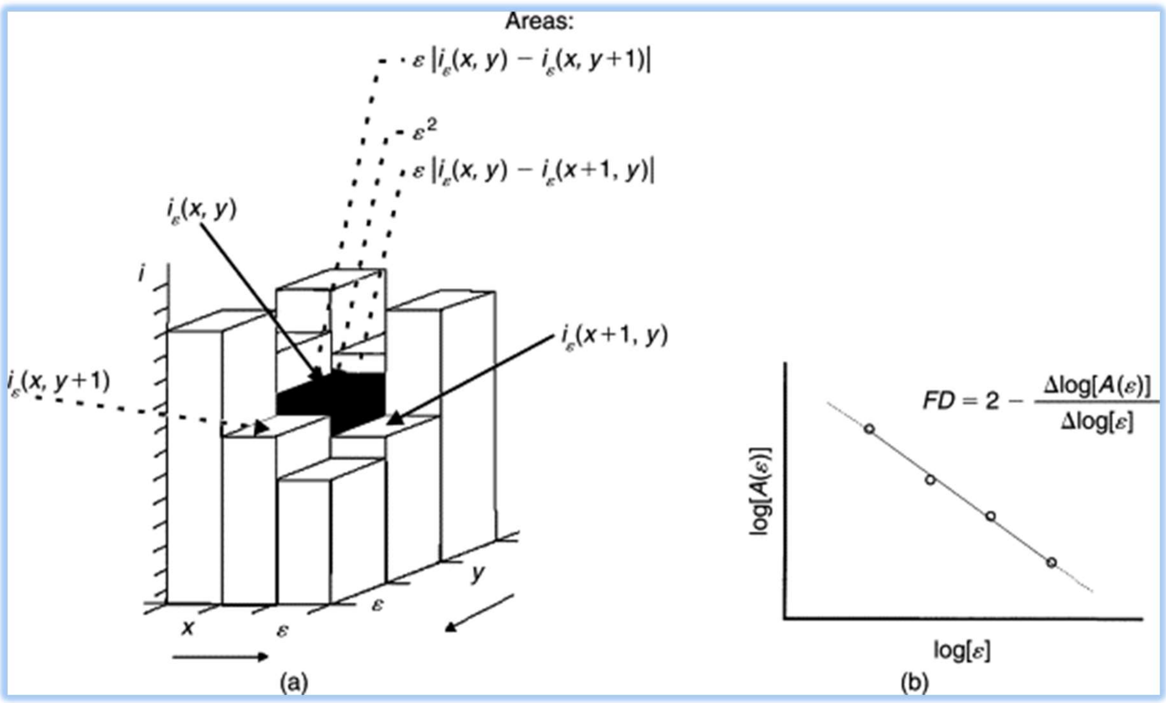
$$A(\varepsilon)=\sum_{x,y}\varepsilon^2+\sum_{x,y}\varepsilon(|i_\varepsilon(x,y)-i_\varepsilon(x,y+1)|+|i_\varepsilon(x,y)-i_\varepsilon(x+1,y)| \quad (4)$$

Because the relationship for fractal image comparisons in a 2-dimensional image can be expressed by the power-law relationship between $A(\varepsilon)$ and ε (Yaffe & Boyd, 2009), the fractal dimension can be determined by:

$$FD_{\text{pixel proximity}}=2-\Delta\log[A(\varepsilon)]/\Delta\log[\varepsilon] \quad (5)$$

Figure 6

Calculation of A(ε) in the Measurement of Fractal Dimension and b) Depiction of the Regression Model of log[A(ε)] vs log[ε] in the Measure of Fractal Dimension



Note. Source: Yaffe and Boyd (2009).

Although Yaffe and Boyd's (2009) work was used to find photographic patterns of self-similarity to detect breast cancer, the approach extends to finding behavioral alignment patterns across organizations. My study applied equation 5 to dimensionality calculations by converting the degree of alignment for a given dyadic pairing to a grayscale image whose pixel count was proportional to the degree of alignment expressed by a dyadic pairing. Ultimately, the two-dimensional grayscale image was evaluated using FDEstimator software provided by the Virtual Fractal-Lab (http://www.fractal-lab.org/Downloads/FDEstimator.html). The software calculated the fractal dimension by calculating the slope of the log[A(ε)] vs log[ε] curve, as shown in Figure 6(b).

I calculated FD using both the replication (Equation 3) and pixel proximity (Equation 5) methods for each respondent and assessed the correlation between both dimensionality methods and reported OC success. Following the fractal dimension calculations, the data was exported back to Minitab for correlative analysis and the assessment of my research question.

Addressing the Research Question

Fractal dimension may eventually lead to a novel method to quantify the alignment of organizational hierarchies during change by evaluating their self-similarity and self-replication. However, prior to this study, the premise was untested in organizational change research. I framed my research question to be a proof of concept for a larger fractal emergence theory. For this study, I questioned if the fractal dimension relating to hierarchical alignment during OC could be measured and if FD was related to organizational change success.

I used Minitab to perform a two-tailed statistical interpretation using Pearson's product-moment correlation test to assess the relationship between fractal dimensionality and OC success. I evaluated the Pearson correlation coefficient *r* to a significance level of $p < 0.05$, indicating a 5% chance to make a Type I error. The *r* was used to indicate the nature of the linear relationship between fractal dimension and organizational success. Because I used two methods to determine fractal dimension, each was tested using the Pearson product-moment correlation method, and the research question was also interpreted using each method.

There are five fundamental assumptions about using a Pearson's product-moment correlation test (Lund Research, 2013; Warner, 2012). The first two relate to the data, namely that they are continuous and that there is a paired relationship between the predictor and criterion variables. The nature of my survey data collection satisfied both of the criteria. The third assumption of the Pearson's correlation is that there is a linear relationship between the predictor and criterion variable. I created a scatterplot to confirm the relationship between both fractal dimension calculations and perceived OC success. Because SOFT predicts that energy usage in a system is not linear. I reasoned that a linear scatterplot might not provide a satisfactory result. Therefore, my research plan was to transform the predictor and criterion variable data using a nonlinear transformation if the scatterplot indicated that the relationship between predictor and criterion was nonlinear (see M. C. Sullivan & Wegman, 1995) or to use a classification and regression tree (CART) analysis to infer the correlation (see Gey & Nedelec, 2005). My contingency plan to transform nonlinear data was to manipulate the variable to reveal linear relationship that might be present using a nonlinear scale. For example, transforming a lognormal relationship between bivariate data will reveal a linear relationship between predictor and criterion variables. Alternatively, CART analysis uses patterns of recursive partitioning to describe associations between variables that is insensitive to normality (Barlin et al., 2013; Nafis et al., 2021). Minitab software is capable of both nonlinear transformations and CART. However, the latter would result in a correlative measure without a corresponding statistical measure of significance. Nonlinear transformations and CART analyses were planned to be used only if linear statistical methods failed to provide a significant result. The fourth assumption of a correlation test is that there are no significant outliers. Therefore, I reviewed the scatterplot to look for outliers. If I discovered an outlier in the data, I planned to review the dataset to ensure there was no transcription error. However, if the outlier represented a valid response from a participant, I planned to include it in the analysis. I discussed the implications of missing data and outliers in Chapter 4. The fifth assumption of correlative analysis is bivariate normality. I tested both the predictor and criterion variables by calculating the descriptive statistics for each variable. I also tested for normality using an Anderson-Darling normality test and a probability plot with 95% confidence intervals to help me find possible outliers. Because I was conducting a bivariate correlation, I did not anticipate the need to analyze covariance.

I conducted a bivariate linear regression analysis following the correlation analysis with fractal dimension as the independent variable and OC success as the dependent variable. I then evaluated the regression model summary for statistical significance. For an alpha risk of $\alpha = 0.05$, a significance value of $P<0.05$ was considered statistically significant. I also evaluated the R^2 value described in the model summary. Because I used two methods to calculate FD, I calculated separate linear regressions for each fractal dimension method, using the R^2 term in the model summary to help explain which method explained the most variation within the survey dataset. Because both fractal dimension calculations were statistically correlated with OC success, the higher R^2 value from a statistically significant regression was helpful in determining which fractal dimension calculation method explains more of the hierarchical alignment data from the study sample. I also reviewed the ANOVA table from the linear regression analysis to verify the significance of the fit. Notably, that I did not require a Bonferroni correction for my regression analysis because I only compared two variables (Laerd Statistics, n.d.).

Threats to Validity

Validity describes the effectiveness of an instrument to measure what it is intended to measure. In this section, I discuss the threats to internal, external, and construct validity for my study.

Internal Validity

Petursdottir and Carr (2018) described internal validity as a research design and data analysis ability to draw accurate conclusions about the relationships between variables. In the context of this study, internal validity refers to using the proper study design to assess correlations and the ability of the instrument and analysis to test the research hypothesis. Onwuegbuzie (2000) outlined 22 common threats to internal validity in a research project. Among the threats outlined in the author’s list, the most relevant for my study were maturation, selection, behavior, and order bias. I discuss these biases and my plan to mitigate them below.

Maturation Bias

Maturation bias occurs when participants become less attentive to their answers due to the passage of time. One of the limitations of my survey instrument is that it was long, containing 38 questions with ten additional demographic questions. I anticipated that the survey would take approximately 30 minutes to complete, but I reasoned that it would likely take longer for some candidates. I also anticipated that some participants would lose interest in providing thoughtful answers over the survey duration and that their attention might drift or dissipate. If so, the questions asked near the end of the survey would be answered with a different level of thoughtfulness than those provided at the beginning. To address this threat to validity, I included multiple questions for each of the creolization and resistance to change subcategories and randomized the order of questions provided to the participants. A randomized presentation of questions helped distribute the uncertainty in maturation and response attentiveness over the entire population of question. Question randomization also helped avoid habituation bias from similarly worded questions and obviated a question-order bias. However, the long survey length still contained some risk of maturation bias, which I discuss in Chapter 5.

Selection Bias

Selection bias occurs when a sampled population is selected based on a trait or characteristic that may not be present in the intended population (Marczyk et al., 2005). I had initially intended to solicit participants from professional societies, reasoning that it would make it easier to target and solicit volunteers. However, I later rejected that plan because of the threat of solicitation bias. A disadvantage of sampling solely from homologous professional societies is that it could lead to over- or under-representation of portions of the true population. For example, Pold and Ivie (2019) revealed that almost 80% of American Astronomical Society (AAS) members held a Ph.D. or were currently pursuing their doctorate. The American Institute of Aeronautics and Astronautics report showed that its membership reflected the age, gender, and job roles typically seen in North American aerospace companies but revealed that it underrepresented the industry's racial diversity (AIAA, n.d.-b). I reduced the self-selection bias inherent in sampling from professional societies by including social media self-selection. By calculating the sample size and ensuring that my dataset of valid surveys contained at least the minimum sample size calculated for the three different aspects of my research design, I also helped mitigate some of the risks of sampling bias.

Behavior Bias

Onwuegbuzie (2000) described behavior bias as the participant's premeditated view of the subject or treatment that prevents their impartial appraisal of the variables. Self-selection bias is a form of behavioral bias related to the motivations and attitudes of volunteers who choose to participate in a study. Behavioral bias is the condition where volunteers have an ulterior motive for participating in a study (Keiding & Louis, 2018). Mansour et al. (2006) noted that survey participants with behavioral bias tended to express their opinions by skewing survey answers to an extreme level, for example, by answering every question at its maximum or minimum value. Therefore, a behavioral bias could invalidate my study's analytical results. Although there was a risk of behavioral bias my self-selected survey, I mitigated some of the behavioral bias risks by omitting surveys that had answers with all "0"s or all "10"s from my calculations.

Self-Sampling Bias

Self-sampling is appropriate for my sampling method because I sought participants with work experience in North American aerospace companies. There was no easy way to contact and recruit participants except through social media or their respective professional societies. However, the disadvantage of self-selection sampling is that it can include self-selection bias. For example, if the participants had a particular grievance with their organization, they could use the survey process to express their dissatisfaction (Leedy & Ormrod, 2010, p. 29). Self-selection bias is a specific form of behavioral bias and posed a distinct threat to the internal validity of my work. However, I attempted to mitigate some of the risks of self-selection bias by sampling from a broad range of social media sites. I also ensured that my response demographics represented the demographics of the overall North American aerospace population.

Order Bias

Order bias is related to maturation bias because it describes the tendency for participants to respond differently to questions based on the order they are presented (Onwuegbuzie, 2000). For example, if I listed all five of the transactional costs in the order they were listed in the variables table, the participants could infer my intent for asking the questions and adjust their responses based on their responses to the previous question. Similarly, it is reasonable to expect that in a long survey, the participant may be less thoughtful about answering at the end of the study than they were at the beginning. I addressed order bias by randomizing the survey questions and by using prevalidated creolization and resistance to change surveys that assessed themes using several questions.

Statistical Conclusion Validity

Statistical conclusion validity refers to the ability of the researcher to assess the relationships between reliable data variables. Two types of errors are common in statistical analysis. The first is a Type I error in which the researcher rejects the null hypothesis and accepts the alternate hypothesis when the null hypothesis is true. The second statistical conclusion error is a Type II error where a researcher accepts the null hypothesis when it is not true. I addressed the threat of a statistical conclusion validity error by ensuring that I obtained a large enough sample size with sufficient statistical power from a reliable sample group. I also used a reliable instrument with validated constructs and analyzed the data using the appropriate statistical tests. Because my study was correlational, I was careful to avoid inferring causality. My nonexperimental design did not use a truly random sample and was incapable of proving causality between predictor and criterion variables.

Another threat to the statistical validity of my research was my treatment of non-responses. My survey was voluntary, and I learned nothing about the people who did not respond (Appelbaum et al., 2019). A sufficient sample size helped assuage some of the risks of non-response (Rose & Fraser, 2008). However, the generalizability of the survey results was limited to those who voluntarily responded. I was also careful to monitor the nonresponses within the datasets I collected for signs of nonresponse bias to specific questions in my survey. If nonresponses within the dataset threatened the statistical significance of my conclusions, I planned to use multiple imputations to address the missing data per the method described by Rose and Fraser (2008). Fortunately, I did not have a significant issue with internal dataset nonresponses, because the use of multiple imputation processes would have further eroded the generalizability of my conclusions.

External Validity

Warner (2012) described external validity as the ability for the results from a study to be generalizable beyond the participants. Onwuegbuzie (2000) characterized 12 threats to external validity in research designs and data collection. Selecting from the authors' list, the external validity threats most relevant to my study were (a) the specificity of variables, (b) temporal validity, and (c) population validity. I will discuss each of these threats and describe my plans to mitigate them below.

Specificity of Variables

The specificity of variables is a threat to external validity in almost every study. Specificity of variables refers to the fact that surveys are taken from a unique set of circumstances that may prevent the study results from being generalizable beyond its specific circumstances and test conditions (Onwuegbuzie, 2000). The more exclusive the participant membership and the more sensitive the participant responses are to the time or context of the test conditions, the lower the generalizability of the findings. To address the threat of specificity, I utilized two surveys that were previously validated for use in organizational change measures. Both the Ai et al. (2019) and Li et al. (2016) studies created operationally defined variables in a way that had meaning outside their study. Duman and Inel (2019) reported that most social research utilizes survey studies to assess quantitative relationships between variables; however, most used individual parametric analyses to evaluate a specific observable response variable. As such, the authors cautioned that the conclusion's validity relies on the participants' understanding of the questions' context.

In addition to challenges with participant comprehension, the researcher must make assumptions about the context of the responses and their representativeness to the study's conclusions (G. M. Sullivan, 2011). Because a survey instrument typically involves a limited population cross-section, most survey research has limited generalizability beyond the narrowly defined terms of the investigation (Duman & Inel, 2019). Because I surveyed North American Aerospace organizations' participants, my results cannot be generalized beyond my study group without additional research. However, because my study was a proof-of-concept exploration of the use of fractal dimension, there was no need to generalize the results beyond the group studied. It sufficed to determine if the fractal dimension applied to the sampled group and whether the use of FD positively addressed my problem statement. I was careful about describing the generalizability of my conclusions beyond the sampled population in the discussion of my findings.

Temporal Validity

Temporal validity refers to the reliability and generalizability of results over time (Onwuegbuzie, 2000). In the context of my experiment, temporal validity applies in two ways. The first temporal validity issue was that I conducted my study during a unique, socially impactful event. I collected data from participants during the global coronavirus pandemic, which had affected how businesses and people act. Some of the participants were likely to have reported about OC programs that occurred during the pandemic, and it is difficult for me to speculate how the temporal context of the pandemic might have affected the responses to my survey questions. A second temporal threat to external validity is that it was designed to include people who have completed or were in the process of completing a change process. Therefore, not all the respondents had completed their change, and not all those who completed their change completed it within the same timeframe. For example, a participant could refer to a change that occurred a decade ago, while another respondent could have just started the change process. Bagnaresi et al. (2018) described the possibility that a respondent's perspective of change success was evolutionary and contextually linked to its moment in time. Simply stated, the respondent's view of the success or failure of a given OC program could change over time. I mitigated temporal validity risks by using the demographic variable DI9 as a data pivot to analyze outliers if they appeared in my analysis.

Population Validity

Onwuegbuzie (2000) described population validity threats as those resulting from the analysis of data subsets. Each subset analyzed reduces the generalizability of the results compared to the overall population. My instrument was capable of subdividing groups by their ethnicity, age, or other demographics. If I attempted to generalize the fractal dimension correlation results for specific demographic groups, I would not have a sufficient sample size to support the correlation analysis. Referring back to my sample size calculation for correlation, I required a minimum of 113 respondents in each demographic category in order to generalize the results for that demographic. To mitigate the external validity threat from population subsampling, I did not determine correlative relationships for subsamples.

Additional population threats to the external validity in my study were non-responsivity and careless responding (Schroeders et al., 2021). My conclusions and their generalizability assumed that there was no difference between those willing to participate and those who were not. Therefore, if the volunteers who participated in my survey were not a fair representation of the North American aerospace community, my conclusions could be skewed. For example, if the people who self-selected to participate in the fractal emergence survey were also more optimistic about aerospace professions than those who did not belong to social media groups, my solicitation of participants from social media sites could have introduced bias. It is possible that people with bad aerospace OC experiences were less likely to join an aerospace social media site than those who viewed aerospace with a positive outlook. Therefore, my solicitation of volunteers from aerospace social media sites could have created an inadvertent nonresponse bias. If social media website members were more positive and optimistic about their views of aerospace and were more likely to respond to the survey than those with negative views of aerospace, it would reduce the validity of my results with respect to the overall North American aerospace community. I mitigated some of the risk of nonresponse bias by soliciting from multiple social media sites.

Careless nonresponse bias was another population threat to my study's generalizability. If the participants felt that the survey was too confusing or too long, the respondent could have become careless about answering the questions correctly or may not have responded to specific questions (see Schroeders et al., 2021). Every careless response or non-response lowered the power of the study to assess the relationships between variables. I mitigated this risk by performing a missing data analysis with a contingency to use multiple imputation to address nonresponses if they it exceeded 15% of the overall dataset, as described by Lang and Little (2018). Multiple imputation overcomes mean substitution biases (Brick & Kalton, 1996) and is applicable for predictor, criterion, or demographic variables (Lang & Little, 2018). However, multiple imputation cannot correct careless responses. To address carelessness due to boredom or duration, I randomized the survey questions to distribute the temporal uncertainty over the entire question population.

Construct Validity

Construct Validity refers to the experimental design, instrumentation, and analytical approach. A valid construct connects operating reality with a research method that allows the researcher to infer legitimate conclusions from the variables in a study (Koehler, 2020). Onwuegbuzie (2000) proposed that instrumentation validity was the single largest threat to construct validity. Koehler (2020) described two additional construct validity threats that were relevant to my study: (a) use of statistical tests that lack sufficient power and (b) equating trivial effects with meaningful ones. In this section, I will describe each of these threats to construct validity in the context of my study and will discuss my plans to address them.

Instrumentation Validity

Instrumentation validity describes the ability of the research instrument to measure the intended effect. Instrumentation validity relates to the construct, content, and criterion reliability of the survey instrument. Corritore et al. (2020) demonstrated that valid survey instruments could satisfactorily capture an individual's beliefs and behaviors regarding their working culture and environment. As such, a survey instrument was appropriate for my research purpose because it was intended to capture beliefs and behaviors within an organizational change paradigm. However, my fractal emergence instrument was only appropriate if it was valid.

I addressed the instrumentation validity risk by using two surveys that had been previously validated for organizational change research. The construct and predictive validity of the creolization scale and its associated subscales were also outlined by Lewis (2003) and analyzed using the methods proposed by Bollen and Diamantopoulos (2017). Similarly, the content, construct, and criteria validity of the change resistance survey elements were validated by Li et al. (2016) using a thorough process of empirical testing, expert input, and examination of the literature. Although I modified the wording of the original surveys to suit my organizational change research interest, I did not fundamentally change the nature of the questions nor their validity for determining creolization and resistance to change, respectively. Ultimately, I reconfirmed the fractal emergence instrument validity when I analyzed the survey responses. In Chapter 4, I described the process I used to reassess and confirm the fractal emergence subscale and overall internal reliability using Cronbach's α for subscale measures with an objective of a Cronbach's $\alpha \geq 0.75$ for a sufficient level of internal reliability. In both the Ai et al. (2019) and Li et al. (2016) studies, the validated measurement coefficients were sufficient to ensure insensitivity to the homogeneity of variance and heteroscedasticity. I reconfirmed this finding in Chapter 4.

Insufficient Statistical Power

The authors from both of the surveys used in this study demonstrated that their respective instruments had sufficient statistical power. However, my conclusions regarding the research question depended on my ability to assess alignment of beliefs and actions regarding OC across an organizational hierarchy using FD. I ensured that I had sufficient statistical power to draw inferences from my study by considering the necessary sample size using three methods and by selecting the most conservative value. To ensure adequate statistical power to determine the correlation between fractal dimension and OC success, I increased the power value used to calculate the sample size from a typical 0.8 to a more conservative value of 0.9.

From an instrumentation standpoint, my study had sufficient statistical power to see an effect. However, the determination of fractal dimension was unprecedented in social research. Therefore, the most significant threat to the external validity of my study regarding statistical power was the risk of incommensurable paradigms (see Wells & Stage, 2015). Although I equated concepts of creolization and change resistance to fractal measures, there was a risk that behaviors and beliefs during OC were not self-replicating values. Because my study was the first of its kind in social research, there was a paradigmatic risk that the terms and ideas relating to OC were not understood or expressed the same way as described by SOFT. It was also possible that the terms and phrases used to assess creolization and change resistance were not equally understood across the organizational hierarchy or across several organizations. Put simply, SOFT theory paradigms might have not translated to the measurement or management of organizational change. To address the threat of incommensurable paradigms, I grounded my research using established principles of physics and organizational change theory. I also addressed my study paradigm shortcomings in the conclusions section of Chapter 4.

Equating Statistically Significant Effects With Meaningful Ones A researcher might mistakenly interpret a statistically significant p-value as confirmation that the relationship between predictor and criterion variable is meaningful when it is not. Koehler (2020) described how the use of a p-value tended to dominate analyses despite the fact that a result that a statistically significant could be practically irrelevant. Sharma (2021) wrote that many types of medical research could not be reproduced even though they showed statistical significance. A p-value provides evidence for the statistical significance of an analysis but does not its verify that the result is meaningful. Equating a statistically significant but low correlation coefficient in my study would diminish the credibility of the research and invalidate the usefulness of my construct. Therefore, I selected a sample size for the Pearson's product-moment capable of detecting effects larger than 0.3, thereby necessitating a correlation with a moderate or strong effect to mitigate this risk. By scoping my study to look for moderate effects or greater, I avoided characterizing small effects (<0.3) as meaningful, despite their statistical test significance as confirmed by a p-value.

Ethical Procedures

Because my study involved human subjects, ensuring the ethical treatment of the participants in this study was my responsibility and utmost priority. I also had an ethical responsibility to ensure that the data I collected, analyzed, and interpreted were trustworthy, statistically defensible, and correctly interpreted. Ethical research with human subjects for my study began with the selection of my research design and through the consideration of informed consent (see Fisher & Anushko, 2008). Prior to any solicitation for participants or the collection of live data, my research was reviewed and screened for ethical behavior. I became CITI certified to perform ethical research at the doctoral researcher level. My research proposal was reviewed by three experienced dissertation chair members to further ensure that my proposed study met the Walden University standards for ethical research. Following the dissertation chair approval, the final research proposal and my CITI certification was reviewed by an internal review board for ethical practice. The internal review board to ensured that my survey design and research method did not expose the participants to any undue social, professional, or emotional risk. Only after successfully completing each of these steps was I permitted to execute my research plan.

However, my responsibility to follow ethical research procedures did not end with the approval of my study. I ensured that my recruitment and solicitation of volunteers did not vary and utilized the preapproved candidate invitation splash page (Appendix X). During the collection phase of my study. I ensured that the participants completed an anonymous online implied consent process occurred prior to collecting any data for the study. I did not require names or identity-compromising demographic identification from the participants and did not collect information regarding the identity of the participant.

After the candidate selected the link provided in the survey invitation letter, they were directed to the online SurveyMonkey platform. Prior to admission to the survey, I required the candidate to verify their eligibility for the study. The candidate was asked to read and agree to a letter of implied consent before they were granted access to the fractal emergence survey. The implied consent statement informed the participant of the research project, its goals, and the length of the survey. The implied consent form also contained a brief explanation of what was expected of the participant's effort. After the candidate affirmed their implied consent, they became a participant in the study. The consent statement also helped inform the candidate of their rights of refusal and described how their identity and anonymity would be protected. The consent form provided information to the participant about their right to opt-out and their right to skip any question they did not feel comfortable answering. At no time was the person's name, IP address, nor any other personally identifying information collected or stored. The participants were also informed that they had the right to review and edit their responses before the final submission. The implied consent form also provided participants with information about who to contact if they had any concerns about their treatment or experiences during their participation. I ensured acknowledgment of consent through the use of a checkbox for the candidate to affirm that they understood and agreed to participate before granting them access to the survey questions.

After the survey was complete, the participant was directed to a debriefing web page where they were thanked for their participation and reminded of the safeguards imposed for the protection of the survey data. They were also given a link to the final report publication site so that they could refer to the study after its completion if desired. Before exiting the survey, the participants were given one last chance to remove their submission and opt-out of the survey. Participants were fully informed of their right to participate or withdraw from the study. If participants wished to contact me, my contact information was made available through a one-way anonymity filter provided by the survey tool service. However, I was not contacted by any participants during the data collection process.

I protected the survey data by restricting access to the survey results—only my chair and I had access to the participant self-response data while it was being collected. After the survey response timeframe had concluded, the raw data was downloaded to my Bitlocker encrypted hard drive. The data files stored on the SurveyMonkey website were deleted and the survey was closed. The downloaded datafile will be kept in digital form on my password-protected computer. A backup of the archive data will be stored on an encrypted, password-protected an Amazon web services cloud server. Following the publication of this study, the dataset generated during my study will be stored in a safe location for five years to comply with Walden University's data retention and security policies. The digital data will be archived on the Amazon web services encrypted cloud server for five years following publication, after which it will be deleted using a DoD 5220.22 equivalent software destruction tool.

Conclusion

The purpose of this study was to explore whether fractal patterns of beliefs and expressed attitudes across organizational hierarchies were indicators of organizational change success. If fractal emergence was discernible through self-replication, this study could provide a way to measure a seemingly stochastic system like an aerospace company undergoing OC in terms of a fractal dimension. A simplified measure and description of OC progress could eventually lead to better OC management and increased organizational change success. This chapter discussed the methodology of the study and outlined and defended my choice of quantitative methods to objectively assess the presence of fractal patterns using a survey instrument. I provided the rationale for my analytical and analysis methods as the best means to answer my research question and hypotheses.

Given the broadness of the potential applicability of SOFT to social science and the lack of existing fractal studies in OC, I limited my inquiry to a proof of concept for the applicability of FD to OC success. I rationalized that a fractal emergence framework for describing OC using SOFT must begin with a general appraisal of the feasibility of the FD concept. Although there were several research designs that could have been used to assess my research question, I selected a quantitative correlative survey using a survey to collect data. The ability of survey instruments to reach a large number of people and provide representative cross-sections of the North American aerospace community made it ideal as a means by which to assess fractal dimensionality. To determine a general result for the population of North American aerospace workers with sufficient power, I determined that I needed more than 113 valid survey responses.

The guiding principle of my research was to ensure that I collected quality data without compromising the ethical treatment of the participants. I described how I ensured informed consent from as well as the safeguards I used to protect the identity of the respondents and to protect the data itself. My data analysis plan contained details about the benefits of my research design and the limits to validity of my study. I described how I prepared for many of the foreseeable contingencies regarding my methodology. Although I studied a relatively unexplored topic in OC research, I am confident that my method allowed me to address my research question and was capable of assessing if whether fractal patterns were present ass an associative factor in organizational change success.

Chapter 4: Results

The purpose of my study was to examine the nature of fractal patterns in OC and to determine whether the FD relating to hierarchical alignment in an organization is correlated with successful change. My review of the extant scholarly literature revealed a gap among researchers who proposed the possibility of fractal behavior and evidence-based research attempting to prove whether self-replicating behavior is present in OC. Based on the literature review, it appeared that my research was the first attempt to examine whether a fractal property could be quantified and correlated with outcome success.

This study was based on the degree by which beliefs, behaviors, and intent align across organizational hierarchies during a change. Alignment can be measured as a combination of the degree of creolization and the resistive intent of the workers, managers, and executives working in an organization. The independent variables for the quantification of creolization were identity multiplicity (IM), cultural hybridity (CH), boundary spanning (BS), and network expansion (NE). The independent variables relating to resistive intent were loss aversion (LA), transactional costs (TC), social norms (SN), affective inertia (AI), behavioral inertia (BI), cognitive inertia (CI), and resistive intent (RI). Using the resistive intent and creolization survey responses from aerospace workers, I calculated a FD for each participant as a unique independent variable and examined whether there was a viable association between the FD and OC success.

In this chapter, I include an overview of the data collection strategy and the associated metadata corresponding to response rates, demographics, and methods for data screening and data cleaning. I then provide an overview of the general statistics for my results, including a confirmational factor analysis of the survey results, general descriptive statistics of the responses, a statistical analysis of the FD fit, and hypothesis testing results of a bivariate Pearson's, Kendall's tau, and Spearman's rho correlation test. The statistical test I used to answer my research question was the correlation coefficient *r*, resulting from the correlation tests. I summarize my findings and discuss my conclusions at the end of this chapter and describe how my results serve as a transition to Chapter 5.

Data Collection

Time Frame, Response Rates, and Sample Calculations

The sample size required to best represent the North American aerospace community was selected as the maximum value from three calculations. The first was a sample size calculation based on estimating the mean value of a given response for a maximum margin of error (see Del Águila & González-Ramírez, 2014; Karim et al., 2019). Based on the exploratory nature of my research, I accepted a 10% maximum margin of error and determined that I required a minimum of 96 respondents. The second method was to ensure that I had enough samples to identify thematic constructs (see Fugard & Potts, 2015). This method indicated a minimum sample size of 113. The third method I used to predetermine a sample size was to calculate it using G*Power software, selecting an a priori analysis of sample size given a medium Cohen's effect size of 0.3 (see Duesbery & Twyman, 2020) and an alpha risk of 5%. For this calculation, I used a relatively large power value of 0.9 because I wanted to ensure that I would be able to observe the effect in the study sample (see Azam et al., 2021). Using G*Power software (see Faul et al., 2009), I calculated the minimum sample size for a Pearson's correlation study given these parameters. This method resulted in a suggested minimum sample size of 112 survey responses. Therefore, I required at least 113 valid surveys.

Table 2

Demographic Comparison of Fractal Emergence Survey Participants vs. Published AIAA North American Aerospace Demographics

Demographic Category	AIAA Demographics Report	Fractal Emergence Survey Participants (count)	Fractal Emergence Survey Participants (% of total)	Difference between AIAA and Fractal Emergence Survey
By Gender				
Male	Not Reported	80	64%	NA
Female	24.80%	38	30.4%	+ 6%
Other or Not Reported	Not Reported	7	6%	NA
By Age				
Over 55	26.2%	33	26%	+ 0.2%
Under 55	73.8%	92	74%	- 0.2%
By Race				
White/Caucasian	Not Reported	61	49%	NA
Black	9.80%	10	8%	- 1.8%
Hispanic	8.70%	13	10%	+ 1.7%
Asian	8.80%	10	8%	- 0.8%
multiracial or other	Not reported	9	7%	NA
Chose not to answer	Not reported	22	18%	NA

A unique challenge in aerospace research is that it is an insular community. I anticipated that there would be challenges in securing enough respondents to my survey because of the participants' predisposition to secrecy, as aerospace workers tend to have heightened concerns about security and risk (see Couper et al., 2008). I mitigated the risk of not getting a large enough sample size by visiting the social media sites used to gather participants several times a week and refreshing my request for volunteers. The data collection time frame was 31 days, with an option to extend that time frame if I did not obtain a large enough sample. No personally identifying information such as names or IP addresses were recorded. Data collection occurred from January 11 to Feb 11, 2022.
After 31 days, a total of 185 volunteers responded to the survey recruitment request; however, only 155 volunteers gave their consent to participate and were allowed to access the survey itself (83.8%).

Data Cleaning and Screening

Of the 155 volunteers who consented to participate in the survey, 26 respondents failed to complete the survey beyond the demographic information. These 26 survey responses were eliminated from the data used for analysis. Three respondents filled out the maximum value for each question, and another respondent filled out the minimum value for each question. Because it is doubtful that a survey using reverse-coded variables would include uniformly high or low responses with all values at the maximum or minimum (see Silvia & Cotter, 2021), all four were omitted from the analysis.
After removing the bad surveys from the data set, I determined that 125 surveys remained for further screening and cleaning. A demographic breakdown of the fractal emergence

survey participants and a comparison to published North American aerospace demographic information is shown in Table 2. In comparing the participation demographics of my survey with the AIAA demographics for North American aerospace employment published by Ernst and Young in 2021 (as cited in Feeko & Fuller, 2021), the participation appeared to be representative of the target population. There was a notably higher percentage of female participants reported in my survey (30%) compared to the AIAA reported general population for North American aerospace firms (25%). The slight overrepresentation of female participants may have biased some of the conclusions from this study; however, the influence was less than my proposed 20% threshold for rejection, so all 125 surveys were included in the next step of the screening process. The impact of my inclusion of a disproportionately higher percentage of female participants is discussed later in this chapter.

Because I was able to create unique links to my survey for different social media sites, I was able to track which sites yielded responses while safeguarding participant anonymity. Table 3 shows the number of participants who completed my survey based on the unique invitation link I created for each site. Most respondents were from the professional social media site LinkedIn, (71%).

Because the remaining 125 surveys met my demographic sample size requirement and were above my minimum sample size threshold of 113, I closed the survey from further participation. I then transferred the data from their native SurveyMonkey output to a Microsoft Excel spreadsheet to facilitate FD calculations or to transfer to Minitab or the Statistical Package for Social Sciences (SPSS) to conduct statistical analysis. After downloading the survey data set to Excel, I reviewed the minimum and maximum values for each variable. During the creation of my survey in SurveyMonkey, I found that I had inadvertently shifted the scalar variable range in four of the thematic variables. Although I used an ordinal 11-point scale for all the creolization and resistive intent variables, I discovered that when I assigned the values to the variables in SurveyMonkey, I assigned IM1, RI1, RI2, and RI3 to a 1–11 scale instead of a 0–10 scale. The shift did not change the respondents' answers, which still used an 11-point Likert-like scale from *disagree completely* to *agree completely*. However, if left unaddressed in the data set, the shift would have led to misinterpretation in column comparisons during statistical analysis. Therefore, I cleaned these columns, normalizing their values by subtracting 1 from each affected response, shifting the range from 1–11 to 0–10.

Table 3

Fractal Dimension Survey Demographics: Solicitation Source Participation

Participant Source / Participant Group	Count	Percent of Total
LinkedIn: Defense and Aerospace Group	69	45%
LinkedIn: Aerospace and Security and Defense Technology and Business	33	22%
SurveyCircle	23	15%
Facebook	21	14%
Linked in: Engineering, Manufacturing, Aerospace, Defense, Industrial, Production Jobs Network	5	3%
LinkedIn: Survey Exchange Group	1	1%
Walden University Participant Pool	1	1%

After adjusting and normalizing the scales of the ordinal variables, my next step in data cleaning was to reverse-code the variables LA1, LA2, TC1-5, AF1-3, CI1-3, RI4, and CS1-3. Because these values addressed the negative aspects of change and alignment, cleaning involved subtracting the absolute value of the original value by 10. During the reverse-coding process, blank or missing data were not overwritten or altered. After the reverse-coding process, the screened spreadsheet was exported to Minitab to analyze the data for outliers and conduct a missing data and outlier analysis.

As shown in Table 4, there were 26 missing nondemographic data items within the overall survey response data set. I tested for data outliers in the survey by performing a Dixon's Q outlier test (see Figure 7). Barkley et al. (2020) reported that the Dixon's Q test is capable of discerning deviations in large, interrelated data sets in which there is a possibility of both large and small value outliers in the population.

Figure 7

Outlier Test for Screened Survey Results (A) Test Results, (B) Typical Outlier Plots

Method

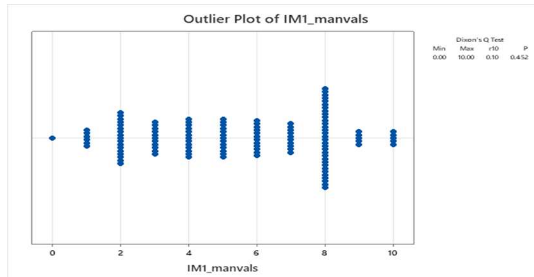
Null hypothesis	All data values come from the same normal population
Alternative hypothesis	Smallest or largest data value is an outlier
Significance level	α = 0.05

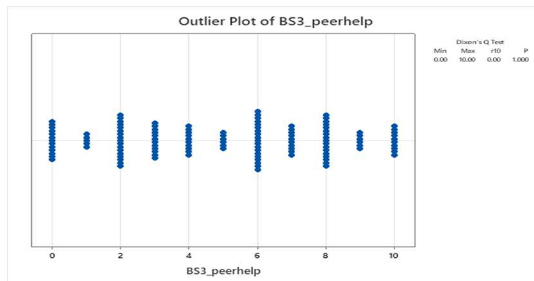
(A) Dixon's Q outlier test results

Variable	N	Min	x[2]	x[N-1]	Max	r10	P
IM1_manvals	125	0.000	1.000	10.000	10.000	0.10	0.452
IM2_commit	124	0.000	0.000	10.000	10.000	0.00	1.000
IM3_equal	125	0.000	0.000	10.000	10.000	0.00	1.000
IM4_vision	124	0.000	0.000	10.000	10.000	0.00	1.000
CH1_orgpract	125	0.000	0.000	10.000	10.000	0.00	1.000
CH2_collchng	125	0.000	0.000	10.000	10.000	0.00	1.000
CH3_indvchng	125	0.000	0.000	10.000	10.000	0.00	1.000
BS1_mgrchat	124	0.000	0.000	10.000	10.000	0.00	1.000
BS2_collegchat	124	0.000	0.000	10.000	10.000	0.00	1.000
BS3_peerhelp	125	0.000	0.000	10.000	10.000	0.00	1.000
BS4_mgmtexp	125	0.000	0.000	10.000	10.000	0.00	1.000
NE1_srvision	125	0.000	1.000	10.000	10.000	0.10	0.452
NE2_exechelp	124	0.000	0.000	10.000	10.000	0.00	1.000
NE3_groupchng	122	0.000	0.000	10.000	10.000	0.00	1.000
LA1_oldadv	125	0.000	0.000	10.000	10.000	0.00	1.000
LA2_oldeff	124	0.000	0.000	10.000	10.000	0.00	1.000
TC1_switchtime	124	0.000	0.000	10.000	10.000	0.00	1.000
TC2_losework	124	0.000	0.000	10.000	10.000	0.00	1.000
TC3_hassle	124	0.000	0.000	10.000	10.000	0.00	1.000
TC4_effortworth	125	0.000	0.000	10.000	10.000	0.00	1.000
TC5_noteasy	125	0.000	0.000	10.000	10.000	0.00	1.000
SN1_colleagthink	125	0.000	0.000	10.000	10.000	0.00	1.000
SN2_mgrthink	125	1.000	1.000	10.000	10.000	0.00	1.000
SN3_substhink	121	0.000	0.000	10.000	10.000	0.00	1.000
AF1_stress	125	0.000	1.000	10.000	10.000	0.10	0.452
AF2_comfort	125	0.000	0.000	10.000	10.000	0.00	1.000
AF3_enjoyold	124	0.000	0.000	10.000	10.000	0.00	1.000
CI1_oldbest	125	0.000	0.000	10.000	10.000	0.00	1.000
CI2_oldeff	123	0.000	0.000	10.000	10.000	0.00	1.000
CI3_oldworks	123	0.000	0.000	10.000	10.000	0.00	1.000
RI1_support	125	0.000	0.000	10.000	10.000	0.00	1.000
RI2_cooper	125	0.000	0.000	10.000	10.000	0.00	1.000
RI3_intendcomply	124	0.000	0.000	10.000	10.000	0.00	1.000
RI4_notneed	124	0.000	0.000	10.000	10.000	0.00	1.000

x[i] denotes the ith smallest observation.

* NOTE * No outlier at the 5% level of significance





(B) Typical outlier plots for the fractal emergence survey categories (IM1 and BS3 shown)

The null hypothesis in Dixon's Q method states that all values come from the same normal population. Therefore, a *p* value above 0.05 allowed me to reject the null hypothesis and accept that there were no outliers at the 5% level of significance. The table from the analysis is shown in Figure 7. All *p* values were above the 0.05 threshold, and I concluded that there were no significant outliers in my data set. However, to be thorough, I also reviewed the outlier plots for each group of variables for unusual patterns. None were detected. Although all outlier plots were analyzed, the outlier plots for IM1 and BS3 are included in Figure 7.

Having confirmed that there were no apparent outliers in the data set, the next step in my data cleaning and screening process was to address the missing data within the remaining responses. Jakobsen et al. (2017) described multiple imputation as a process that begins with understanding the data and the impact of missing data in a given study. Jakobsen et al. advised that when the missing data represent less than 5% of the overall survey responses, it may be best to accept the missing data and use them within the complete case analysis. Table 4 shows that the maximum percentage of missing data for any given theme was under 3.2%, which indicated that I could accept the missing data. However, Jakobsen et al. advised that before a case analysis is accepted, the researcher should evaluate the patterns of missing data for randomness and evaluate the impact of the missing data on the dependent variable by substituting the largest and smallest plausible value in each missing data field and conducting a sensitivity analysis.

Figure 8

Percentage Breakdown of Missing Data

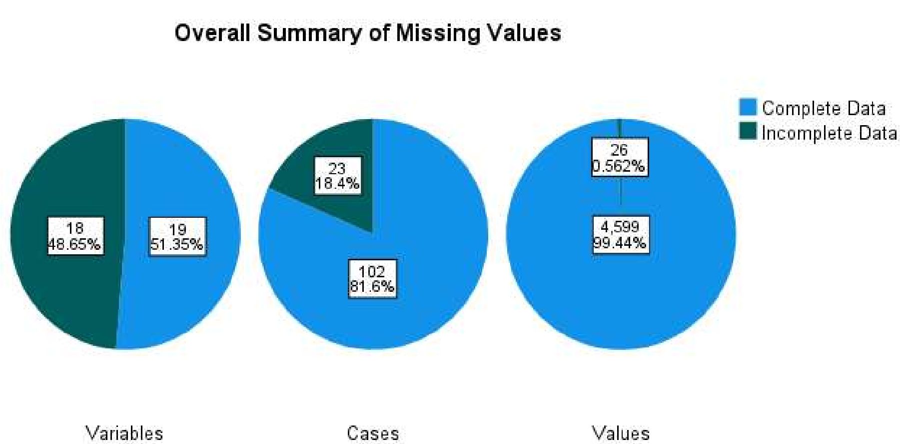


Table 4

Summary of Missing Data in the Fractal Emergence Survey

Variable Summary[a,b]

	Missing		
	N	Percent	Valid N
SN3	4	3.2%	121
NE3	3	2.4%	122
RI5	2	1.6%	123
CI3	2	1.6%	123
CI2	2	1.6%	123
RI6	1	0.8%	124
RI4	1	0.8%	124
RI3	1	0.8%	124
AF3	1	0.8%	124
TC3	1	0.8%	124
TC2	1	0.8%	124
TC1	1	0.8%	124
LA2	1	0.8%	124
NE2	1	0.8%	124
BS2	1	0.8%	124
BS1	1	0.8%	124
IM4	1	0.8%	124
IM2	1	0.8%	124

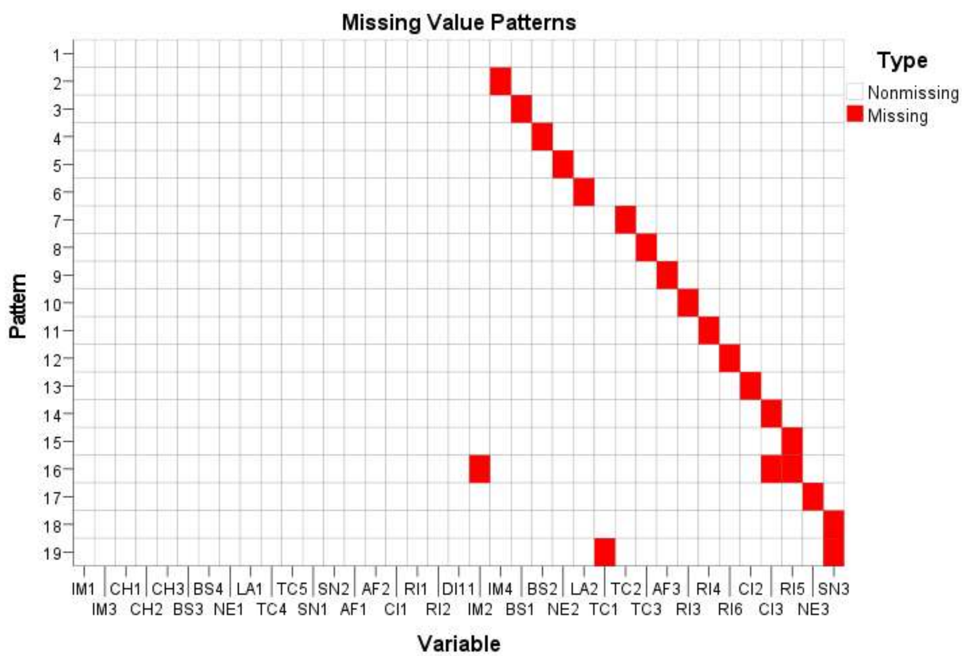
a. Maximum number of variables shown: 50

b. Minimum percentage of missing values for variable to be included: 0.0%

As shown in Figure 8, approximately half (18 out of 37) of the variables contained at least one missing data element. Twenty three of the 125 participants (18.4%) had at least one blank or missing data field. Overall, the 26 missing data fields accounted for 0.5% of the overall data available for analysis. As shown in Figure 9, no pattern to the missing data was apparent. None of the variables appeared to have a consistent pattern of missing data, and it appeared that the most prevalent occurrence of missing data were single field occurrences.

Figure 9

Patterns of Missing Data Fields in the Survey Responses



To determine the sensitivity of the missing data on the predictor and criterion variables, four imputation methods were selected in Minitab. The missing values were included in the FD calculation spreadsheet. Multiple imputations were also included to determine the impact of replacing missing values with imputed values. The four methods selected for the imputation analysis were (a) all values set to response mean for the respondent, (b) all values set to the respondent's maximum value, (c) all values set to the respondent's minimum value, and (d) a random pull from a probability distribution based on the mean and standard deviation of the respondent's answers. The values for each of the creolization and resistance to change themes were calculated for each case of the imputation method. The results for imputation were compared to the same values with the variables left blank. The difference in calculated mean, standard error of the mean, standard deviation, coefficient of variation, and kurtosis were calculated. The overall results are shown in Table 5.

In the first column of Table 5, the mean value of all imputation methods is shown, indicating the likely value for accepting a multiple imputation. In the third through the seventh column, the maximum change from the lowest value imputed to the highest value imputed is shown. Based on the low occurrence of missing data and the correspondingly low improvement in the predictor or criteria variable values obtained by multiple imputation, I elected to leave the missing values in the data set and use the case analysis.

After addressing missing and nonresponse data, I performed an analysis of the descriptive statistics for each predictor and criterion variable, including the mean, standard deviation, range, skewness, kurtosis, and the Anderson-Darling normality test. Prominent in the summary of the basic statistics were the low P-values for the Anderson-Darling normality test (see Table 6). A P value <0.05 for the Anderson-Darling normality test indicated that the response data for a variable in question departed from those expected with a normal distribution. Non-normality was expected in the responses because approximately half of the population reported successful change where most

Table 5

Maximum Impact of Substitution of Missing Variables Using Multiple Imputation vs. Leaving Blank

		Maxiumum difference created in all imputations				
Mean of all 4 methods	Predictor Variable	Δ Mean	Δ SE Mean	Δ SD	Δ CoefVar	Δ Kurtosis
5.391	**Ave IM**	0.017	0.001	0.017	0.450	0.030
1.057	**Stdev IM**	0.021	0.001	0.005	1.070	0.270
NA	**Ave CH**	0.000	0.000	0.000	0.000	0.000
NA	**Stdev CH**	0.000	0.000	0.000	0.000	0.000
5.187	**Ave BS**	0.031	0.000	0.004	0.280	0.010
1.375	**Stdev BS**	0.035	0.002	0.022	0.530	0.370
5.569	**Ave NE**	0.054	0.001	0.012	0.430	0.000
1.395	**Stdev NE**	0.073	0.006	0.060	0.750	0.250
4.919	**Ave LA**	0.022	0.001	0.012	0.050	0.030
0.983	**Stdev LA**	0.025	0.003	0.027	0.970	0.660
4.654	**Ave TC**	0.029	0.002	0.018	0.280	0.030
1.543	**Stdev TC**	0.024	0.002	0.019	0.560	0.080
5.970	**Ave SN**	0.075	0.002	0.022	0.550	0.030
1.434	**Stdev SN**	0.097	0.008	0.082	1.370	0.460
3.817	**Ave AF**	0.012	0.002	0.018	0.270	0.010
0.778	**Stdev AF**	0.016	0.001	0.005	1.770	0.250
3.302	**Ave CI**	0.043	0.002	0.019	1.290	0.030
0.776	**Stdev CI**	0.070	0.017	0.181	13.730	8.790
5.360	**Ave RI**	0.016	0.002	0.025	0.420	0.490
2.852	**Stdev RI**	0.024	0.002	0.020	1.030	0.080
Mean of all 4 methods	Criterion Variable	Δ Mean	Δ SE Mean	Δ SD	Δ CoefVar	Δ Kurtosis
5.279	**Mean Success**	0.042	0.001	0.007	0.320	0.020
0.987	**Stdev Success**	0.049	0.007	0.071	4.210	0.460
1.161	**D by Pixel**	0.005	0.000	0.002	0.280	0.230

Note: Four imputation methods used.

1) Maximum value, 2) Minimum Value, 3) Mean Substitution, 4) Random selection from probability distribution

Table 6

Basic Statistics of the Cleaned and Screened Survey Dataset Variables

Variable	Mean	SE Mean	s	CV	Skewness	Kurtosis	MSSD	AD	P
CS3	5.12	0.22	2.45	47.87	-0.10	-0.89	6.89	1.81	<.005
IM1	5.46	0.23	2.62	47.89	-0.17	-1.18	7.44	3.31	<.005
IM2	5.58	0.24	2.72	48.74	-0.19	-1.05	8.07	2.62	<.005
IM3	5.06	0.23	2.57	50.77	0.12	-0.98	8.10	2.20	<.005
IM4	5.14	0.24	2.68	52.21	-0.09	-0.99	8.13	1.94	<.005
CH1	5.47	0.24	2.71	49.54	-0.18	-0.85	8.15	1.36	<.005
CH2	5.70	0.24	2.70	47.41	-0.18	-1.18	8.32	2.95	<.005
CH3	5.56	0.25	2.78	50.01	-0.10	-1.14	8.47	2.59	<.005
BS1	5.13	0.27	2.98	58.14	-0.12	-1.05	10.23	1.65	<.005
BS2	5.40	0.26	2.84	52.61	-0.09	-1.06	9.03	2.16	<.005
BS3	4.95	0.28	3.08	62.13	-0.04	-1.16	10.85	2.13	<.005
BS4	5.05	0.25	2.79	55.34	0.11	-0.96	9.20	1.50	<.005
NE1	6.34	0.25	2.76	43.45	-0.35	-1.01	7.37	3.03	<.005
NE2	5.07	0.25	2.74	54.10	-0.02	-0.95	8.24	1.49	<.005
NE3	5.01	0.25	2.78	55.50	0.07	-0.93	9.33	1.65	<.005
LA1	5.02	0.25	2.81	55.93	0.16	-0.74	8.34	1.53	<.005
LA2	4.94	0.26	2.86	57.81	0.03	-0.85	8.89	1.58	<.005
TC1	5.33	0.24	2.70	50.56	-0.08	-0.82	8.34	1.41	<.005
TC2	5.78	0.23	2.53	43.75	-0.16	-0.46	6.62	1.84	<.005
TC3	4.61	0.26	2.84	61.48	0.14	-0.85	9.33	1.92	<.005
TC4	5.35	0.26	2.92	54.59	-0.22	-1.01	9.52	1.93	<.005
TC5	5.18	0.22	2.48	47.91	0.12	-0.37	7.07	1.56	<.005
SN1	5.48	0.24	2.71	49.36	-0.09	-0.82	7.50	1.72	<.005
SN2	6.99	0.21	2.38	34.10	-0.56	-0.54	5.22	2.84	<.005
SN3	5.24	0.26	2.82	53.81	-0.05	-0.99	8.28	1.61	<.005
AF1	6.26	0.22	2.50	39.89	-0.16	-0.94	6.26	2.53	<.005
AF2	5.91	0.24	2.63	44.55	-0.05	-0.93	6.91	2.05	<.005
AF3	6.23	0.24	2.72	43.64	-0.30	-0.66	7.71	2.14	<.005

Table 6 (Continued)

Variable	Mean	SE Mean	s	CV	Skewness	Kurtosis	MSSD	AD	P
CI1	6.54	0.24	2.63	40.13	-0.26	-0.83	6.67	2.91	<.005
CI2	6.63	0.23	2.58	39.00	-0.38	-0.77	6.78	2.55	<.005
CI3	6.60	0.24	2.66	40.25	-0.36	-0.85	6.84	3.02	<.005
RI1	5.51	0.26	2.87	52.12	-0.04	-1.06	8.70	2.22	<.005
RI2	6.07	0.27	3.04	50.07	-0.30	-1.21	8.96	4.24	<.005
RI3	6.25	0.26	2.88	46.15	-0.30	-1.13	7.69	3.39	<.005
RI4	5.40	0.28	3.08	57.08	-0.11	-1.13	10.52	2.68	<.005
CS1	5.20	0.28	3.08	59.11	0.03	-1.07	10.26	1.93	<.005
CS2	5.39	0.28	3.11	57.72	-0.01	-1.14	11.18	2.14	<.005
CS3	0.48	0.04	0.50	104.50	0.08	-2.03	0.31	22.34	<.005

Note: SE = Standard error, s = Standard deviation, CV = Coefficient of variation,

MSSD = mean of the squared successive differences, AD = Anderson-Darling statistic

Likert-type scores would be high, and approximately half of the population reported unsuccessful change practices where the Likert-like scores were expected to be low. Therefore, an aggregate measure of the variables was unlikely to demonstrate the properties of a normal distribution. Having addressed the missing variables and after I determined to leave the missing variables unadjusted, my next step was to establish the internal consistency of the questions used in the survey and compare them to the original authors' results.

I first placed all the thematic variables into Minitab and SPSS and built a structural equation model (SEM) using the analysis of moment structures (AMOS) software add-on for SPSS. Due to the large number of ordinal data in my dataset, the AMOS/SPSS model could not resolve the number of iterations required to perform the

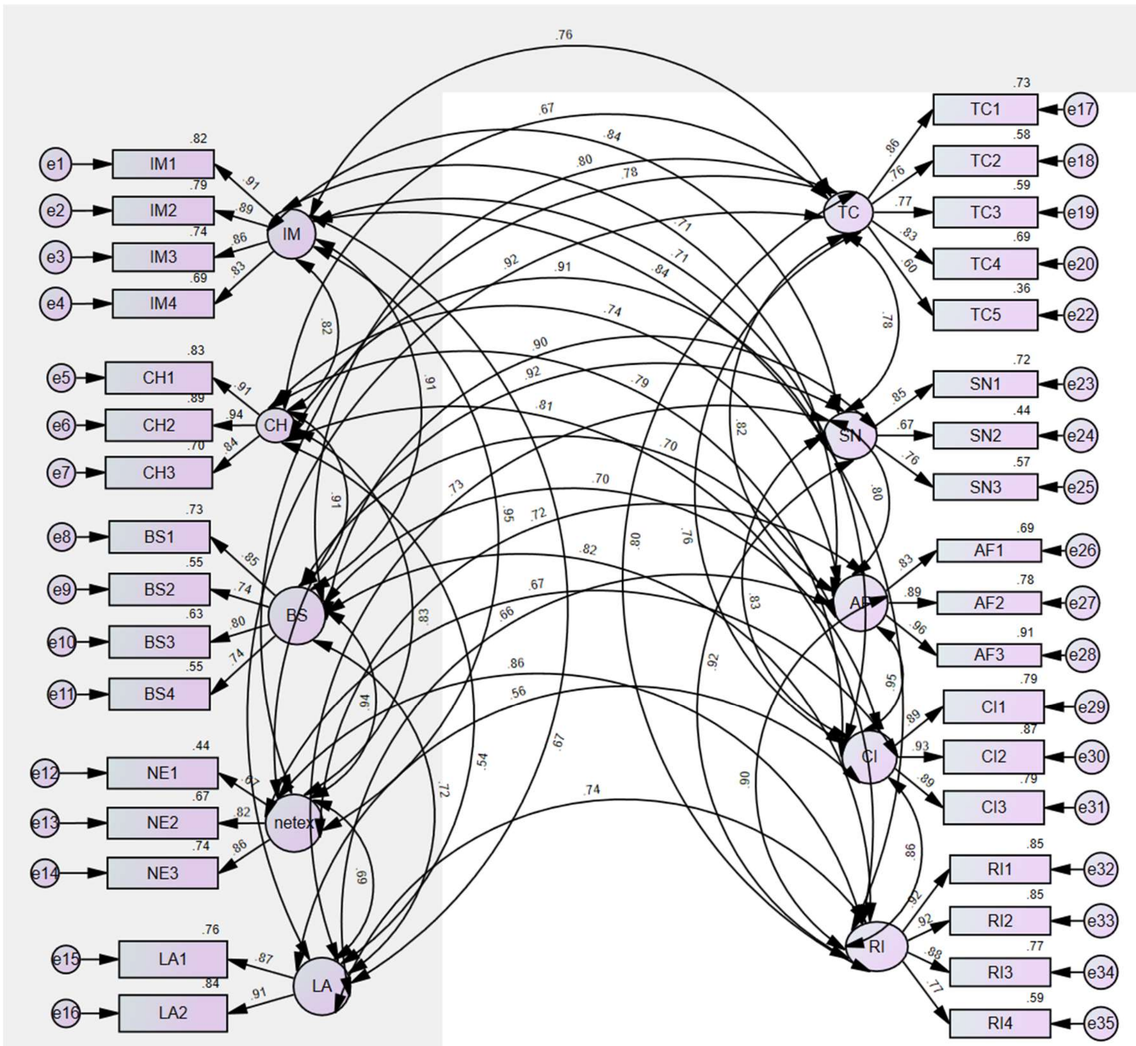
CFA. Therefore, I changed the ordinal values to interval data as described in the variable table (Table 1). The consequences of converting the ordinal values to interval data in a CFA is that it increased the likelihood of making a Type II error (Wang, et al., 1999). However, Robitzsch (2020) suggested that for a CFA model fit using and wide ordinal scale, that errors with assumed normality were minimized when the model fit was strong. I used an 11 point Likert-like scale for my ordinal data which reduced the risk of error in factor analysis (see Wu and Leung, 2017). Because the purpose of my CFA analysis was to reconfirm the validity of two previously validated instruments, I reasoned that there was minimal risk of misinterpretation of the CFA resulting from my interval level data conversion.

After I converted the ordinal values to continuous variables, the SEM for the CFA could proceed. The large number of factors in my dataset prevented AMOS from being able to determine the means and intercepts for any themes with missing data in my survey responses, so I removed the 23 lines of data associated with missing responses leaving 102 remaining survey responses. The lowered sample size fell below the value of N = 113 I had originally planned for my study. I used G*Power software to estimate the post hoc impact of the lowered sample size on my analysis. The reduction in sample size for a correlation strength above 0.3 with a sample size of N=102 lowered the statistical power to determine correlations to 0.871, which was still above the 80% recommended power for exploratory analysis (see Araujo & Frøyland, 2007). However, Jobst et al. (2021) cautioned that low sample sizes combined with a large number of factors made the interpretation of SEM highly questionable. Because my purpose for SEM analysis was to reconfirm the validity of existing surveys, I elected to proceed with the SEM analysis. However, I based on my ordinal data transformation and small sample size, I concluded that my SEM offered support that my fractal emergence survey maintained its validity instead of definitively proving that the survey itself was valid.

With the discrete data analyzed as continuous data and the missing data omitted, the CFA analysis was able to resolve to a minimum and provided an estimate of correlations and covariances for the factors. The standardized effects calculated for the correlations between the themes and their questions and the covariance between themes are shown in Figure 10. However, before the analytical relationships could be accepted as, I needed to review the integrity of the overall model. AMOS provided a Chi-Square test for overall model independence to assess the relationship between the variables in the CFA. The model showed a high Chi-Square value and a correspondingly low P-value. Therefore, from the Chi-Square results, the model does not provide sufficient evidence to conclude that there is a statistically significant proportional difference between the covariance matrix and the implied covariance matrix. The proportions did not differ for fractal emergence covariance by $\chi^2(482, 113) = 1058$, $p < 0.001$.

Figure 10

Structural Equation Model of the Fractal Emergence Survey for CFA



However, for large, complex CFA models, Chi-Square is not always a reliable predictor of model fit (Stickl Haugen et al., 2021), particularly if the data are not normally distributed (Zhang et al., 2021). Therefore, I also considered the comparative fit index (CFI) and the Tucker-Lewis index (TLI) to assess the structural equation model

(Table 7). The CFI and TLI values are slightly below the 0.90 value conventionally attributed to a good SEM fit (Suárez-Colorado et al., 2022). Furthermore, the root mean square error of analysis (RMSEA) for the model shown in Table 8 is slightly above the maximum 0.10 threshold conventionally attributed to a good SEM fit (Marsh et al., 2004). However, the wide confidence interval for the default model provides for values between 0.10 and 0.12.

Table 7

Baseline Comparison of Model Fit Indices

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.756	.716	.851	.823	.848
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Table 8

Baseline Comparison of RMSEA of Model RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.109	.100	.118	< 0.001
Independence model	.260	.253	.267	< 0.001

The CFA results were not surprising considering my reduced sample size and my conversion of the data from ordinal to interval values. The root mean square error of approximation RMSEA was .109, and when I considered the confidence interval for the RMSEA, my overall mean analysis error could have been between 10% and 12%. The RMSEA was not ideal for a close CFA model fit but was within the range of an acceptable fit for an experimental model. Therefore, I chose to keep the model for comparative purposes to show the correlations and covariances between the thematic factors. My next step was to review the factor reports from the CFA to assess the internal consistency of the factors and model.

The regression weights (Table 9) for the CFA show the unstandardized factor loadings for the SEM. All the factors were significant to .05 level of significance, as indicated by the three asterisks in the P column. Because the SEM analysis loads each indicator variable onto a single factor, I interpreted the standardized loadings to be a rough approximation for the correlation between the factor and its corresponding themes. All the correlated loadings were well above 0.70, indicating a potentially strong correlation between the individual questions and their corresponding theme. Because the model fit was not very strong, I cannot conclude that the high loadings are proof of survey validity. However, large, standardized factor loadings are a good indication that the subcategories were consistent and indicated good consistency with their respective thematic constructs.

The covariance table (Table 10) contains the covariances between the latent factors in the structural equation model used in the CFA. The P-values were all below the 0.001 threshold, indicating a statistically viable covariance between the themes. All of the covariances were positive, indicating that as one theme increased, the other theme increased by the corresponding amount. The covariance ratio (CR) is the ratio of the covariance value and the standard error of estimate. Because the CR was greater than the average estimate for each covariant pair, I inferred that it was a reliable covariance (see Evermann, 2012).

Table 9

Regression Weights of Unstandardized Loadings for the Thematic Factors in the SEM

Factor Loading			Estimate	S.E.	C.R.	P	Label	Standardized Estimate
IM4	<--	IM	0.974	0.820	11.869	< 0.001	par_1	0.832
IM3	<--	IM	0.957	0.740	12.869	< 0.001	par_2	0.863
IM2	<--	IM	1.032	0.740	13.882	< 0.001	par_3	0.890
IM1	<--	IM	1.000					0.907
CH3	<--	CH	0.921	0.760	12.156	< 0.001	par_4	0.837
CH2	<--	CH	1.009	0.620	16.355	< 0.001	par_5	0.941
CH1	<--	CH	1.000					0.912
BS4	<--	BS	0.807	0.910	8.913	< 0.001	par_6	0.744
BS3	<--	BS	0.959	0.970	9.898	< 0.001	par_7	0.795
BS2	<--	BS	0.826	0.093	8.887	< 0.001	par_8	0.742
BS1	<--	BS	1.000					0.854
NE3	<--	NE	1.295	0.169	7.670	< 0.001	par_9	0.860
NE2	<--	NE	1.206	0.164	7.341	< 0.001	par_10	0.816
NE1	<--	NE	1.000					0.666
LA2	<--	LA	1.000					0.914
LA1	<--	LA	0.973	0.076	12.730	< 0.001	par_11	0.873
TC1	<--	TC	1.000					0.855
TC2	<--	TC	0.837	0.091	9.178	< 0.001	par_12	0.759
TC3	<--	TC	0.931	0.100	9.340	< 0.001	par_13	0.767
TC4	<--	TC	1.032	0.097	10.670	< 0.001	par_14	0.832
TC5	<--	TC	0.636	0.096	6.615	< 0.001	par_15	0.600
SN1	<--	SN	1.000					0.848
SN2	<--	SN	0.710	0.094	7.587	< 0.001	par_16	0.665
SN3	<--	SN	0.929	0.102	9.117	< 0.001	par_17	0.756
AF1	<--	AF	1.000					0.833
AF2	<--	AF	1.162	0.101	11.539	< 0.001	par_18	0.885
AF3	<--	AF	1.259	0.095	13.244	< 0.001	par_19	0.955
CI1	<--	CI	1.000					0.887
CI2	<--	CI	1.046	0.070	14.928	< 0.001	par_20	0.933
CI3	<--	CI	1.001	0.075	13.282	< 0.001	par_21	0.889
RI1	<--	RI	1.000					0.921
RI2	<--	RI	1.030	0.064	16.096	< 0.001	par_22	0.920
RI3	<--	RI	0.947	0.067	14.107	< 0.001	par_23	0.879
RI4	<--	RI	0.890	0.085	10.433	< 0.001	par_24	0.768

Table 10

Covariance Table for the CFA

			Covariances (Group number 1 - Default Model				
Factor Association			**Estimate**	**SE**	**CR**	**P**	**Label**
CH	<-->	BS	5.725	0.972	5.893	<.001	par_25
CH	<-->	NE	3.714	0.754	4.928	<.001	par_26
CH	<-->	LA	3.401	0.781	4.354	<.001	par_27
IM	<-->	CH	4.570	0.794	5.753	<.001	par_28
IM	<-->	BS	5.423	0.923	5.878	<.001	par_29
IM	<-->	NE	4.024	0.774	5.198	<.001	par_30
IM	<-->	LA	3.985	0.787	5.061	<.001	par_31
BS	<-->	NE	4.490	0.889	5.052	<.001	par_32
BS	<-->	LA	4.804	0.939	5.117	<.001	par_33
NE	<-->	LA	3.277	0.732	4.474	<.001	par_34
IM	<-->	TC	4.094	0.764	5.358	<.001	par_35
IM	<-->	SN	4.445	0.792	5.610	<.001	par_36
IM	<-->	AF	3.333	0.651	5.124	<.001	par_37
IM	<-->	CI	3.754	0.719	5.218	<.001	par_38
IM	<-->	RI	5.278	0.896	5.888	<.001	par_39
CH	<-->	TC	3.782	0.765	4.945	<.001	par_40
CH	<-->	SN	5.059	0.862	5.867	<.001	par_41
CH	<-->	AF	3.660	0.696	5.256	<.001	par_42
BS	<-->	AF	3.710	0.765	4.930	<.001	par_43
BS	<-->	CI	4.225	0.837	5.046	<.001	par_44
BS	<-->	RI	5.795	0.033	5.611	<.001	par_45
NE	<-->	TC	3.336	0.715	4.668	<.001	par_46
NE	<-->	SN	3.906	0.781	5.002	<.001	par_47
NE	<-->	AF	2.695	0.600	4.488	<.001	par_48
NE	<-->	CI	2.863	0.649	4.412	<.001	par_49
LA	<-->	CI	3.304	0.752	4.395	<.001	par_50
NE	<-->	RI	4.329	0.860	5.036	<.001	par_51
LA	<-->	TC	5.477	0.926	5.913	<.001	par_52
LA	<-->	SN	4.329	0.844	5.130	<.001	par_53
LA	<-->	AF	3.454	0.710	5.864	<.001	par_54
LA	<-->	RI	5.167	0.953	5.424	<.001	par_55

Note: SE = Standard error, CR = Covariance ratio

Table 10 (Continued)

Covariances (Group number 1 - Default Model

Factor Association			Estimate	SE	CR	P	Label
TC	<-->	SN	4.166	0.799	5.212	<.001	par_56
SN	<-->	AF	3.757	0.710	5.290	<.001	par_57
AF	<-->	CI	4.453	0.756	5.893	<.001	par_58
CI	<-->	RI	5.410	0.916	5.903	<.001	par_59
AF	<-->	RI	4.965	0.849	5.845	<.001	par_60
SN	<-->	RI	5.749	0.966	5.949	<.001	par_61
TC	<-->	RI	5.064	0.913	5.545	<.001	par_62
SN	<-->	CI	4.413	0.798	5.533	<.001	par_63
TC	<-->	CI	4.065	0.769	5.288	<.001	par_64
TC	<-->	AF	3.880	0.720	5.390	<.001	par_65
CH	<-->	CI	4.426	0.791	5.592	<.001	par_66
CH	<-->	RI	5.381	0.930	5.789	<.001	par_67
BS	<-->	TC	4.830	0.906	5.328	<.001	par_68
BS	<-->	SN	5.375	0.952	5.647	<.001	par_69

Note: SE = Standard error, CR = Covariance ratio

Table 11 contains the correlation estimates and the squared multiple correlations for the thematic variables. Although the overall model reliability was low, there appears to be a strong correlation between the factors. All the correlations were positive, and all were above 0.5. The squared multiple correlations are analogous to the R-squared in linear regression and can be thought of as the percentage of variation explained by the thematic factor (Evermann, 2012).

Table 11

(A) Correlation and (B) Squared Multiple Correlations for the CFA

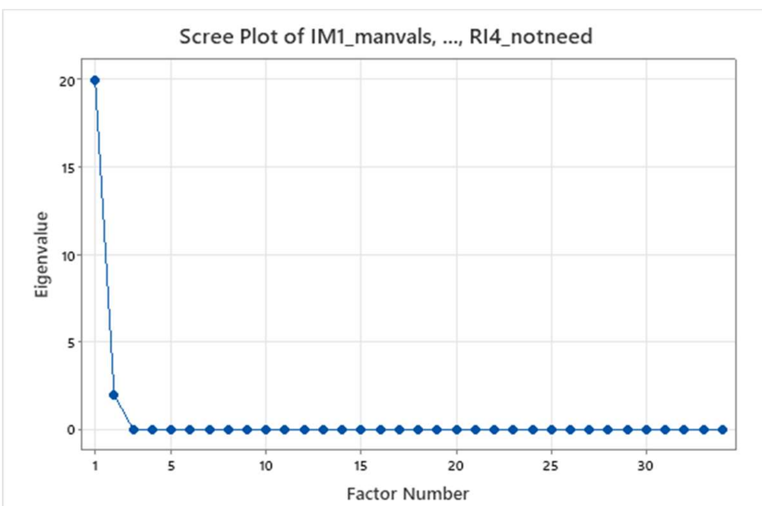
(A) Between Factor Correlation Estimates			Estimate
CH	<-->	BS	0.907
CH	<-->	NE	0.829
CH	<-->	LA	0.545
IM	<-->	CH	0.817
IM	<-->	BS	0.906
IM	<-->	NE	0.947
IM	<-->	LA	0.673
BS	<-->	NE	0.937
BS	<-->	LA	0.719
NE	<-->	LA	0.691
IM	<-->	TC	0.764
IM	<-->	SN	0.842
IM	<-->	AF	0.711
IM	<-->	CI	0.706
IM	<-->	RI	0.843
CH	<-->	TC	0.669
CH	<-->	SN	0.909
CH	<-->	AF	0.74
BS	<-->	AF	0.701
BS	<-->	CI	0.704
BS	<-->	RI	0.82
NE	<-->	TC	0.777
NE	<-->	SN	0.924
NE	<-->	AF	0.718
NE	<-->	CI	0.672
LA	<-->	CI	0.557
NE	<-->	RI	0.863
LA	<-->	TC	0.915
LA	<-->	SN	0.734
LA	<-->	AF	0.66
LA	<-->	RI	0.739
TC	<-->	SN	0.781
SN	<-->	AF	0.805
AF	<-->	CI	0.947
CI	<-->	RI	0.862
AF	<-->	RI	0.897
SN	<-->	RI	0.923
TC	<-->	RI	0.8
SN	<-->	CI	0.834
TC	<-->	CI	0.756
TC	<-->	AF	0.819
CH	<-->	CI	0.789
CH	<-->	RI	0.815
BS	<-->	TC	0.799
BS	<-->	SN	0.902

(B) Squared Multiple Correlations: (Group number 1 - Default model)	
Factor	**Estimate**
RI4	0.59
RI3	0.773
RI2	0.847
RI1	0.848
CI3	0.791
CI2	0.871
CI1	0.787
AF3	0.913
AF2	0.784
AF1	0.695
SN3	0.572
SN2	0.443
SN1	0.72
TC5	0.36
TC4	0.693
TC3	0.589
TC2	0.576
TC1	0.731
LA1	0.763
LA2	0.835
NE1	0.444
NE2	0.666
NE3	0.74
BS1	0.729
BS2	0.551
BS3	0.632
BS4	0.553
CH1	0.831
CH2	0.886
CH3	0.7
IM1	0.823
IM2	0.793
IM3	0.744
IM4	0.692

The squared multiple correlations demonstrated that the correlative model fit explained a significant amount of the observed data. Although this did not obviate the poor model fit, the high strengths of association supported the notion that the fractal emergence survey validity was consistent with the creolization and change resistance parent surveys. My conclusion regarding the confirmatory factor analysis is that it was consistent with the authors' original findings of consistency between the questions and themes. However, because the large model was not statistically significant and fell just outside the recommended values for fit, I needed to conduct a factor analysis (FA) to confirm my conclusion, followed by an item analysis (IA) to confirm that the fractal emergence survey was valid.

Figure 11

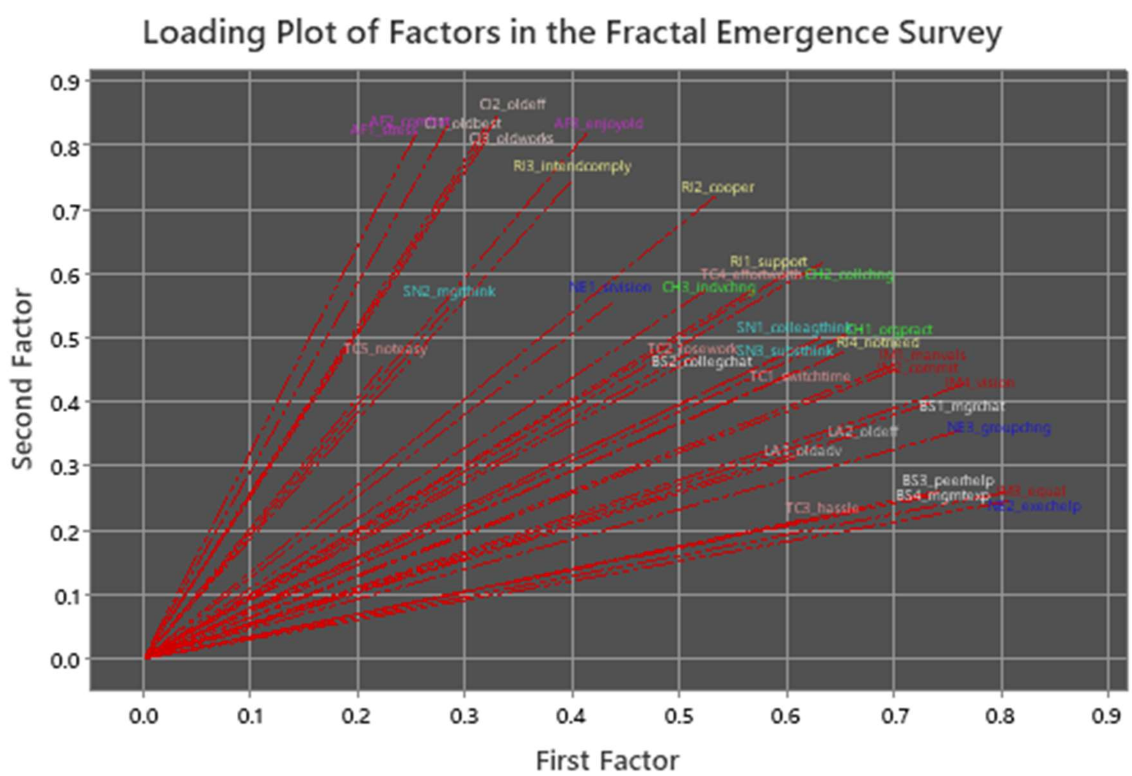
Scree Plot of the Predictor Variables in the Fractal



I used Minitab software to conduct a FA. The advantage of FA was that it did not require the conversion of ordinal data, nor did I need to eliminate rows with missing data to complete the analysis. My first step in FA was to evaluate a scree plot of all the predictor variables using Minitab to determine how many factors to evaluate. Figure 11 shows how the eigenvalues changed as more factors are added to the FA model. Because the eigenvalues dropped off sharply after two factors, I concluded that most of the observed variations in the factor analysis were explained by two factors. I inferred that a two-factor model made sense because the fractal emergence survey was based on two surveys that assessed creolization and change resistance. Having selected two FA factors, my next step was to run a complete factor analysis using a varimax rotation.

Figure 12

Loading Plot for the First Two Factors Identified in the Factor Analysis



The loading plot (Figure 12) shows which thematic variables had the largest effect on the two factor FA model identified in the Scree plot. Note that factor loadings can range in value from -1 to 1. A loading close to -1 or 1 indicates that an item (i.e., a variable) strongly influences the loading factor, and a value of zero indicates that an item has no influence on the component. Consistent with the results from my CFA analysis, it appeared that the fractal emergence survey variables were strong influencers on the survey construct. Although the number of factors in the loading plot make it difficult to pick out individual variables, the chart shows that most of the survey themes had a strong effect on the factor and that the distribution of survey questions relating to fractal emergence were relatively well distributed between two thematic factors, with approximately half of the survey questions relating to the first factor, and the other half more strongly linked to the second factor.

Table 12 contains the rotated factor loadings and communalities for the two-factor FA model. Like the CFA model, the individual factor loadings were loaded onto each factor independently and are indicative of the strength of association between the predictor variable and the FA model factor. The communality value is the sum of square factor loadings for the variables and reflects the proportion of each item's variance that can be explained by the factor itself (Ichikawa & Konishi, 2008). Overall, it appeared that the two-factor model was sufficient to describe the individual survey variables and that the two factor FA model accounted for almost 65% of the variation in the survey results.

Because the fractal emergence survey was derived from two previously validated surveys, I was curious about how the individual thematic factors from each parent survey fit into a two-factor model in the factor analysis. Therefore, I color-coded the data in Table 12. The variables in the first column that are shaded white were those originating from the creolization survey, and the ones shaded gray originated from the resistance to change survey. I used Excel's conditional formatting feature to highlight the highest (green) to lowest (red) values in each of the two factors identified in the model. Because both surveys covered a broad spectrum of organizational change, there appeared to be some overlap in the survey questions. An overlap is where an item from one of the FA model factors had similar variance to another FA model factor. I found it reassuring that the highest variable factor loadings in the first modeled factor were predominantly from the creolization survey and that the second factor was predominantly from the resistance to change survey. Overlapping was expected because both surveys included questions related to how the individual perceived change and assessed the beliefs or actions related to their organization's adoption of the OC. I inferred that the overlapping factors were areas of good general agreement or commonality between creolization and resistance to change themes.

As part of the FA process, I also checked if the two themes correlated with the overall dataset using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity. Both tests were used to indicate whether there was sufficient redundancy in the two-factor prediction to verify the suitability of my data for structure detection. Table 13 shows the results from the Kaiser-Meyer-Olkin (KMO) and Bartlett's test for assessing the factor analysis fit. The KMO measure indicated the proportion of my data that linked to the factors identified, with a score above 0.6 considered acceptable (see Hill, 2011). The Bartlett's test of sphericity determined whether my correlation matrix was similar in structure to an identity matrix, in which case it would have been unsuitable for structure detection (IBM, 2021b). Unlike the CFA fit, the Bartlett's test is considered statistically significant when it has a high value of Chi-Square and a low P-value, indicating that it is significantly differs from an identity matrix. Both the KMO and Bartlett's test measures in Table 14 confirmed that creolization and resistance themes were acceptable for structure detection. The factor analysis also added credibility to the SEM and CFA results and reinforced my conclusions from the CFA results. However, to validate the fractal emergence instrument, I also needed a measure of internal consistency.

Table 12

Rotated Factor Loading and Communalities in the Factor Analysis

Variable	Factor1	Factor2	Communality
NE2_exechelp	0.807	0.245	0.712
IM3_equal	0.802	0.258	0.71
IM4_vision	0.764	0.426	0.765
NE3_groupchng	0.762	0.355	0.707
BS4_mgmtexp	0.741	0.260	0.617
BS3_peerhelp	0.735	0.253	0.604
BS1_mgrchat	0.734	0.398	0.698
IM2_commit	0.702	0.450	0.696
IM1_manvals	0.700	0.457	0.699
LA2_oldeff	0.665	0.349	0.564
SN1_colleagthink	0.654	0.504	0.682
RI4_notneed	0.652	0.477	0.653
TC3_hassle	0.646	0.225	0.468
RI1_support	0.633	0.615	0.779
CH1_orgpract	0.631	0.499	0.647
TC1_switchtime	0.612	0.449	0.576
LA1_oldadv	0.610	0.314	0.47
SN3_substhink	0.604	0.479	0.594
CH2_collchng	0.599	0.597	0.715
TC4_effortworth	0.568	0.574	0.652
RI2_cooper	0.533	0.719	0.801
CH3_indvchng	0.525	0.574	0.605
BS2_collegchat	0.517	0.470	0.488
TC2_losework	0.510	0.476	0.487
NE1_srvision	0.436	0.552	0.494
AF3_enjoyold	0.414	0.818	0.841
RI3_intendcomply	0.399	0.743	0.712
CI2_oldeff	0.330	0.844	0.822
AF2_comfort	0.320	0.807	0.754
CI3_oldworks	0.319	0.826	0.785
CI1_oldbest	0.285	0.833	0.774
SN2_mgrthink	0.285	0.547	0.38
AF1_stress	0.255	0.819	0.735
TC5_noteasy	0.224	0.456	0.258
Variance	11.572	10.372	21.943
% Var	34.0%	30.5%	64.5%

Note: 1st column: Gray shaded = Resistance to change variables, White shaded = Creolization variables.

Table 13

KMO and Bartlett's Test Results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.939
Bartlett's Test of Sphericity	Approx. Chi-Square	4096.662
	df	595
	Sig.	<.001

Having confirmed that the two factors in my survey were relevant in factor analysis, I focused my attention on establishing whether the factors in my instrument were internally consistent using IA to provide a measure Cronbach's alpha. However, Taber (2018) noted that Cronbach's alpha as a single measure of internal consistency can be incomplete in long surveys because the alpha score increases naturally with the number of questions. Given that my survey had 34 thematic questions, I presumed that my survey could be considered longer than most. Taber (2018) prescribed that researchers evaluating Cronbach's alpha with long surveys with many themes should assess internal consistency using individual IAs. Therefore, I conducted a set of progressive item analysis tests, starting with each of the themes, then aggregating the themes into their respective Creolization or resistance to change themes. Following the IA for creolization and resistance to change, I was able to assess the internal consistency of the fractal emergence survey itself. By building the item analysis progressively, I was able to establish the individual Cronbach's alpha values for each progression and ensure that the individual questions were consistent within a theme before assessing the consistency of the overall survey. Appendix D contains the details of each item analysis, including their respective correlations and covariances.

Table 14

Summary of the Cronbach's Alpha Measures of the Fractal Emergence Model as Built Progressively and Tested at Each Iteration

Theme	Number of Questions	Cronbach's Alpha Overall	Maximum value of Cronbach's Alpha if (least impactful terms) are omitted
Identity Multiplicity (IM)	4	0.9317	0.9329 (IM4)
Cultural Hybridity (CH)	3	0.9351	0.9293 (CH3)
Boundary Spanning (BS)	4	0.8754	0.8708 (BS4)
Network Expansion (NE)	3	0.8272	0.8559 (NE1)
Loss Aversion (LA)	2	0.8407	NA - only 2 terms
Transactional Costs (TC)	5	0.8770	0.8774 (TC5)
Social Norms (SN)	3	0.7911	0.7269 (SN3)
Affective Inertia (AF)	3	0.9207	0.9157 (AF1)
Cognitive Inertia (CI)	3	0.9385	0.9124 (CI2)
Resistive Intent (RI)	4	0.9258	0.9404 (RI4)
Overall Creolization (IM --> NE)	14	0.9639	0.9644 (NE1)
Overall Resistance to Change (LA --> RI)	20	0.9677	0.9683 (TC5, SN2)
Overall Fractal Emergence (Creolization and Resistance to Change)	34	0.9792	0.9895 (TC5)

The value of Cronbach's alpha can range in value from 0 to 1. The higher the value, the higher the implied level of internal consistency. Table 15 shows consistently high alpha values for the survey themes, with the social norms (SN) theme showing the lowest alpha at 0.79. All the other thematic variable had a Cronbach's alpha value above 0.8. In the last column of Table 14, I included a missing item alpha value, indicating whether eliminating a question in the survey would improve the overall internal consistency. The only term whose omission improves both the theme, subtheme, and overall fractal emergence alpha score was question TC5. However, its inclusion still provided Cronbach alpha scores in excess of 0.95. Therefore, I retained TC5 as a factor in the fractal dimension calculation. From the progressive testing and the collective results of the IA analysis, especially when I consider the supporting CFA and FA analysis results, I concluded that all variables are sufficiently meaningful and internally consistent.

Calculating the Fractal Dimension and OC Success

Following the testing for internal consistency, I exported the cleaned and screened survey responses to Microsoft Excel to the fractal dimension value for each survey participant. As I described in Chapter 2, I chose to calculate the fractal dimension using two methods because my research interest was exploratory, and I was curious if the FD calculation method mattered regarding an association with OC success.

The first FD calculation evaluated replication across the various themes based on the respondent's level in the organization. The replication based FD measure was calculated using equation 3.

$$\text{Dimension} = FD_{replication} = \log(\text{Copies}) / \log(\text{Scale}) \quad (3)$$

Because the survey asked for individual thoughts and how subordinates, peers, managers, and executives performed in the change process, I evaluated the similarity of thematic answers relative to the dyadic paring of the individual respondent and how their assessment of workers, managers and executives aligned to their individual beliefs and actions. The structure of the survey questions allowed me to assess the alignment between individual-colleague, worker-to-manager, worker-to-executive, and manager-to-executive pairs for each response. The scale referred to the path length of the dyadic landscape and was fixed in the first equation to the maximum path length of four (4) as shown in Figure 5. The copies term consisted of the fraction to which the dyads achieved alignment, as indicated by the proportion by which a dyadic group varied from perfect alignment as indicated by a mean score of 10 for in a particular theme.

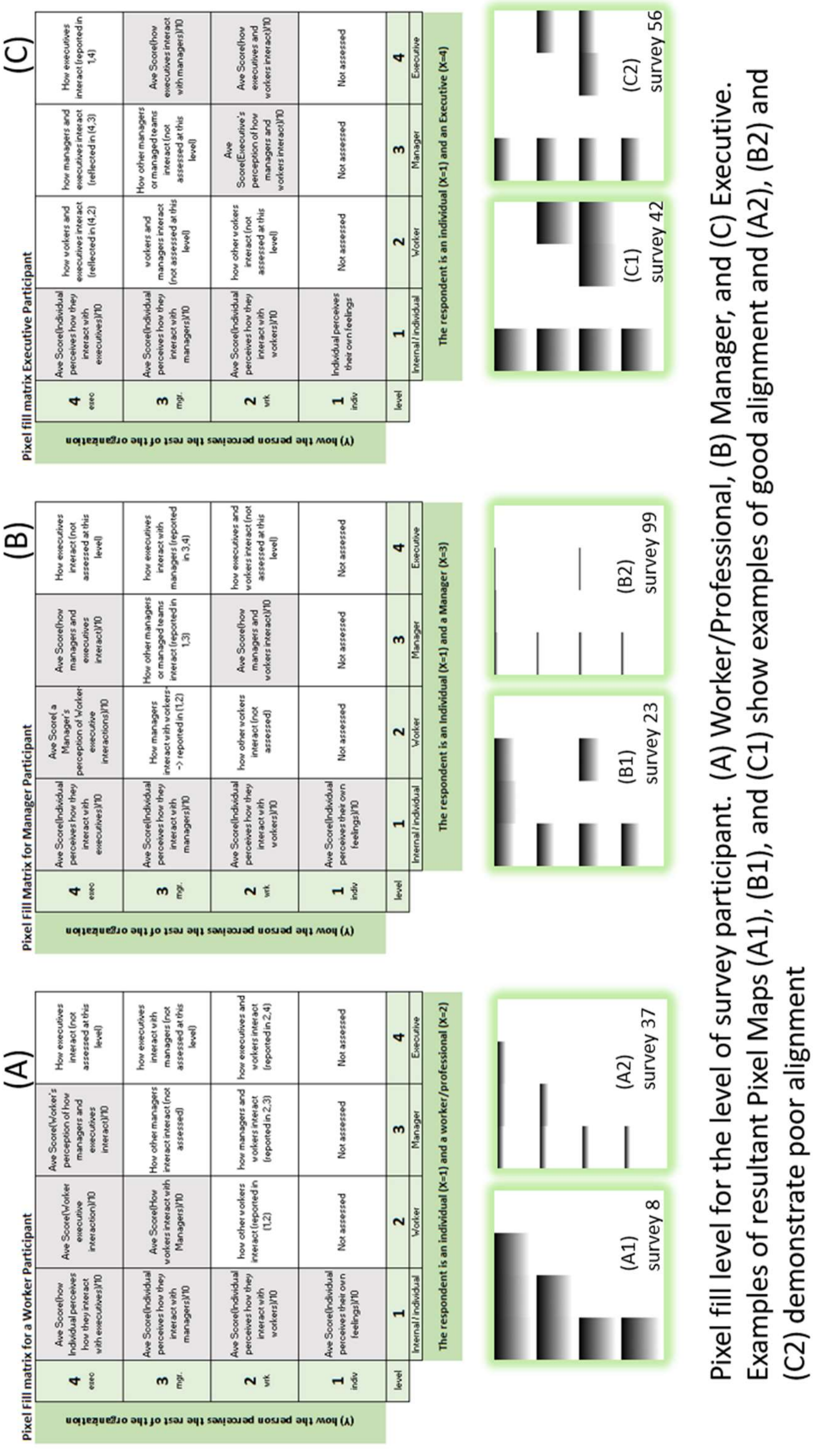
The second measure of dimensionality utilized a pixel-based determination of fractal dimension.

$$D_{\text{by pixels}} = FD_{\text{pixel proximity}} = 2 - \Delta\log[A(\varepsilon)]/\Delta\log[\varepsilon] \quad (5)$$

To calculate the dimensionality using Equation 5, I first had to transform the hierarchical alignment information into a 2-dimensional grayscale image. Because my survey evaluated four levels of hierarchy, I created a 4x4 matrix of boxes, each with a 256x256 pixel area. I then broke each of the thematic questions into their respective category based on the respondent's role in the organizational hierarchy via question DI6. From the respondent's level (X), the corresponding Y-values were associated with the respondent's dyadic relation to the object of the question. For example, if a worker (level 2) answered a question about how a manager (level 3) interacted with workers during a change, the pixel coordinate is (2,3). Several of the fractal emergence survey questions asked how the individual (level 1) felt or acted during the change process. Because an individual belief or behavior was not necessarily the same as how the respondent felt about how other workers, managers, or executives would act, the responses were held at an X=1 coordinate in the pixel matrix creation. A grayscale percentage for each coordinate pixel was determined by calculating the portion of the mean score of the coordinate value relative to a value of 10 (the maximum possible score if there were perfect alignment). Each of the coordinates in the matrix were shaded with a grayscale gradient equivalent to their percentage alignment at each measured dyadic coordinate. Typical examples of high and low images from the survey are shown in Figure 13.

Figure 13

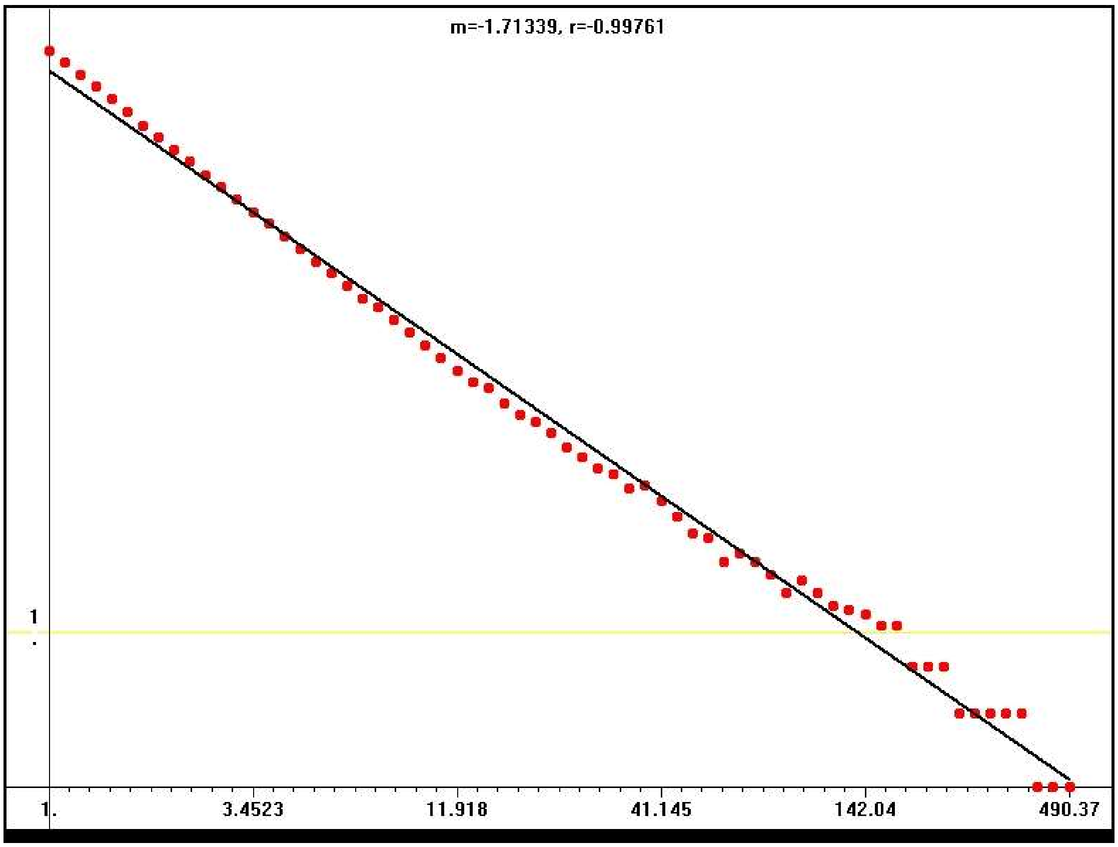
Description of Pixel Coordinates Used in the Pixel-Based Fractal Dimension



I created 125 individual JPEG images using the method described to create the shaded pixel fields necessary to calculate $FD_{by\ pixel}$. To calculate the fractal dimension of each image, I utilized a freeware fractal dimension estimator software package named FDEstimator by the Virtual Fractal-Lab (http://www.fractal-lab.org/Downloads/FDEstimator.html). The FDEstimator software used the "box counting method" to compare multiple pixel fields of various size within a grayscale image. The software worked by overlaying multiple rectangular areas called "boxes" in equal measures along the image and then counted the number of black or gray pixels present in the box (N). The pixel area, A, was determined as the box length multiplied by the box width of the box selected. The software calculated the log(A) and log(N) for that pixel size. It then reduced the size of the boxes and recounted. By iterating box counts in increasingly smaller box sizes, it is able to construct a stable slope for the change in the Log(A) vs. and Log(N). Subtracting the slope of the (Δlog(A) vs. Log (N)) curve from 2 provided the fractal dimension for the image. An example of the box-counting pixel slope method is shown in Figure 14 for a randomly selected survey response (the 89th survey response). Each of the grayscale images for the survey responses and their associated $FD_{pixel\ proximity}$ images are included in Appendix D.

Figure 14

ΔLog(A) vs Log(N) Curve for Survey Response #89



I calculated FD using both the replication (Equation 3) and pixel proximity (Equation 5) methods for each of the cleaned and screened survey responses and copied the results into Minitab to assess my research question. OC Success measures were estimated by calculating the mean value of the change success variables CS1, CS2, and CS3. The FD and OC calculated values were then exported to Minitab to complete the correlation analysis.

Addressing the Research Question

When proposing this study, I hypothesized that the fractal dimension could indicate the organizational alignment during the change process by quantifying the degree of self-similarity and self-replication that occurred across hierarchical boundaries. After data cleaning and screening and after I calculated the FD and OC success for each respondent from the fractal emergence survey data, I was ready to assess my research question:

RQ: Is there an association between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success?

H_0: There is no correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

H_a: There is a statistically significant correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

I used Minitab and SPSS statistical analysis software to perform a two-tailed statistical interpretation using Pearson's product-moment correlation test to assess the relationship between FD and OC success. Table 15 shows the summary statistics of the predictor and criterion variables. Because OC success was measured on a Likert-like scale of 0-10, the mean of 5.2 is not surprising. A completely successful OC process would result in a score of 10 and a completely unsuccessful OC process would result in a score of 0. Because slightly more than half of the respondents reported successful change, the score of 5.2 reflected that the mean score for success was also positive. The standard deviation for the mean reflected a relatively broad assessment of success across the participant population, which was also expected because negative experiences were likely to have correspondingly low scores and positive experiences were likely to have higher scores. The mean values for each predictor variable D(Pixel Proximity) and D(replication) were both below 2, reflecting the fractional degree by which the mean survey responses deviated from a perfect 2-dimensional alignment. Note that using either dimensional calculation method, a "perfect alignment" would result in a maximum value of 2 on an (x, y) comparative scale.

Table 15

Summary Statistics of the Predictor and Criterion Variables

Descriptive Statistics

	Mean	Std. Deviation	N
Mean(OC Success)	5.1813	2.70851	125
D(Pixel Proximity)	1.6994	.09876	124
D(replication)	1.1466	.36160	124

Table 16 shows that the Pearson's correlation between the fractal dimension and mean OC success was relatively high, and the two methods for calculating FD resulted in slight variation in the correlated strength of association to OC success. The correlation between mean OC success and fractal dimension as measured by the replication method (Equation 3) was 0.785. The correlation was positive, indicating that as dimensionality increased, the mean OC success increased. The correlation between mean OC success and fractal dimension as measured by the pixel proximity method (Equation 5) was 0.753. The correlation between $FD_{Pixel\ Proximity}$ and OC success was also positive.

Table 16

Pearson's Correlation Assessment of OC Success and Fractal Dimension

Correlations

		Mean(OC Success)	D(Pixel Proximity)	D(replication)
Mean(OC Success)	Pearson Correlation	–		
	Sum of Squares and Cross-products	909.668		
	Covariance	7.336		
	N	125		
D(Pixel Proximity)	Pearson Correlation	.753**	--	
	Sig. (2-tailed)	<.001		
	Sum of Squares and Cross-products	24.776	1.200	
	Covariance	.201	.010	
	N	124	124	
D(replication)	Pearson Correlation	.785**	.962**	--
	Sig. (2-tailed)	<.001	<.001	
	Sum of Squares and Cross-products	94.491	4.227	16.082
	Covariance	.768	.034	.131
	N	124	124	124

**. Correlation is significant at the 0.01 level (2-tailed).

Because I used two methods to assess the fractal dimension, the close correlation between FD calculated by replication and by pixel method was beneficial as a cross-check to ensure that the results did not depend on the method used to calculate FD. Table 17 shows a very strong relationship between the two fractal dimension calculation methods, with a Pearson's correlation coefficient of 0.962. If both calculation methods were identical, their Pearson's correlation coefficient would be 1.0. The two measurement approaches varied slightly in approach and yielded slightly different strengths of association, but it appears that both were adequate indicators of OC success.

Table 17

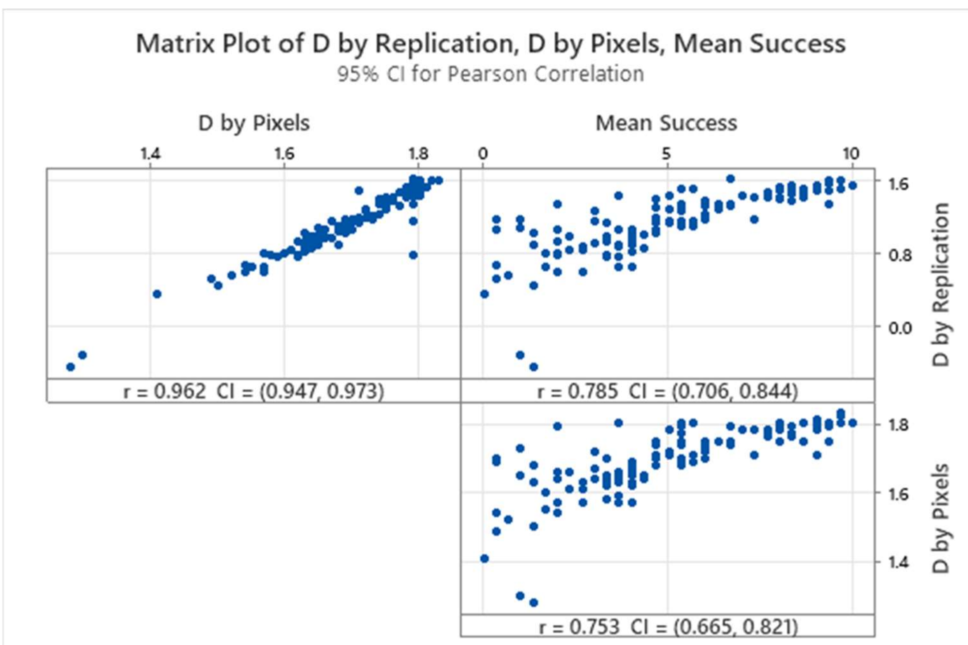
Pairwise Pearson Correlation Table With Confidence Intervals

Pairwise Pearson Correlations

Variable 1	Variable 2	N	Correlation	95% CI for p	p-value
D by Pixels	D by Replication	124	0.962	(0.947, 0.973)	<.001
success	D by Replication	124	0.785	(0.706, 0.844)	<.001
success	D by Pixels	124	0.753	(0.665, 0.821)	<.001

Figure 15

Matrix Plot of the Associations Between Variables Using Pearson's Product-Moment Correlation



However, before accepting the Pearson's product-moment correlation results as conclusive regarding my research question, I had to test the assumptions underlying the

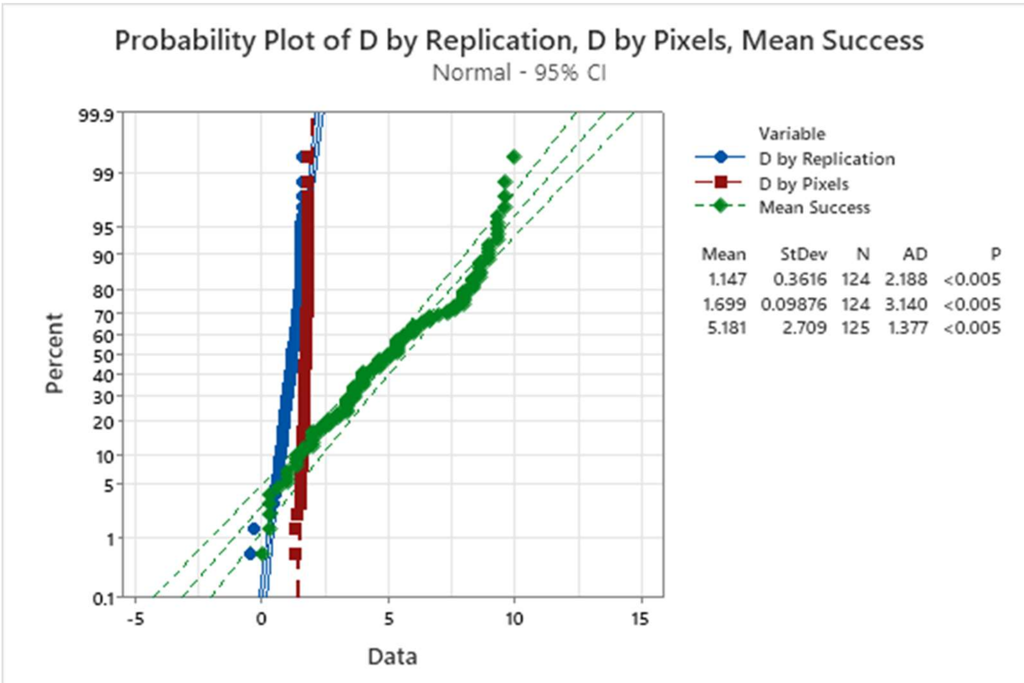
Pearson's correlation test. Warner (2012) stated that a basic assumption of the Pearson's correlation test is that the scores of both the predictor and criterion variables were roughly normally distributed. Warner also asserted that for the Pearson's test to apply, a valid level of measure was required. Warner asserted that the scores of predictor and criterion variables should be linearly related, have roughly equal variance across the measure, and be independent of each other.

To confirm that the relationships between the variables were valid, I created a matrix plot (Figure 15) and observed good general linearity across the scale. I interpreted this to indicate that I had satisfied the requirement of the Pearson's product-moment analysis that there be a valid level of measurement and that the related pairs of values also showed a general linearity. However, I still needed to confirm that the variables were generally normally distributed and homoscedastic of scale (Warner, 2012).

Newson (2002) reported that the Pearson's product-moment bivariate correlation test is robust for data that are not normally distributed if the dataset has a finite variance and covariance. Newson warned that nonparametric data could invalidate the reported P-value used to test for significance. Therefore, before I could accept the Pearson's correlation test results, I had to assess the normality of my predictor and criterion variables. Figure 16 shows that neither the predictor nor criterion variables were normally distributed within a 95% level of significance. The P-values for the Anderson-Darling (AD) normality tests were less than $P=0.05$. Therefore, I rejected the AD null hypothesis and concluded that the dataset exhibited a severe departure from normality.

Figure 16

Probability Plot and AD Normality Test of Predictor and Criterion Variables



Mishra et al. (2019) advised that for datasets with more than 100 observations, the violation of normality is not a significant concern for correlative testing. Because my dataset met the sample size criteria, I inferred that the lack of normality did not obviate the acceptance of the Pearson's correlation test. However, the Pearson's bivariate correlation test also assumes equal variance across the measure. Therefore, I tested for normality of the residuals using tests for equal variance using mean OC success as the criterion variable and FD by replication as the predictor variable. I used a multiple comparison's test and a Levene's test for homoscedasticity (see Figure 17). The null hypothesis in both tests were that the variances between predictor and criterion variables were equal. I conducted two tests for homoscedasticity for each FD calculation method.

The multiple comparisons test is considered a more powerful to assess equal variances than Levene's method (Minitab 18 Support, n.d.). However, the Minitab blogsite advised that when there was a large discrepancy between the two measures, the method associated with the lowest p-value should be used (Minitab 18 Support, n.d.). Therefore, I concluded that the data were not normal, nor were they homoscedastic, and could not reliably assess the association between predictor and criterion values.

Figure 17

Test for Equal Variances Across Measurement Scale

(a) Test for equal variance: Mean OC success and FD by replication

95% Bonferroni Confidence Intervals for Standard Deviations

Sample	N	StDev	CI
D by Replication	124	0.36160	(0.28262, 0.47116)
Mean Success	125	2.70851	(2.47181, 3.02207)

Individual confidence level = 97.5%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	< .001
Levene	226.14	< .001

Test for Equal Variance: Mean OC Success and FD by pixel proximity

95% Bonferroni Confidence Intervals for Standard Deviations

Sample	N	StDev	CI
Mean Success	125	2.70851	(2.47181, 3.02207)
D by Pixels	124	0.09876	(0.07730, 0.12850)

Individual confidence level = 97.5%

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	< .001
Levene	280.53	< .001

The multiple comparisons test returned a value of P<0.001, and the Levene's test showed similar results: $F_{(replication)}$ (1,123) = 226.14, p = <0.001and $F_{(pixel)}$ (1,123) = 226.14, p = <0.001, respectively. Regardless of the measure by which FD was calculated, the tests for equal variance showed that data appeared to be heteroscedastic at the 95% level of confidence. I would not have expected the FD results to be normally distributed, because the values for success and alignment depended on whether the participant viewed the OC as successful. However, I expected that individual responses would be normally distributed around their perceived alignment or success level for their given OC process. Therefore, I expected that the normality for a response from groups of individuals reporting a similar perspective of success would be normally distributed. Testing for the normality of the dataset relative to a participant's perception of success was outside the scope of this investigation. However, I was curious if my expectations for normality when moderated by success score were valid. Therefore, I recalculated normality of FD when controlled for by the OC success level reported and found that most of the data was normally distributed (see Appendix G). However, the lack of normality in the predictor and criterion variables and the lack of homoscedasticity prevented me from axiomatically accepting the Pearson's correlation results.

Although my initial research plan was to test the association between the fractal dimension and OC success using the Pearson's correlation method, the nonparametric nature of the results prevented me from drawing a definitive conclusion for the association using the Pearson's correlation in isolation. Therefore, I also evaluated the correlation between success and fractal dimension using nonparametric measures of association.

Table 18

Nonparametric Correlations of Mean OC Success and the FD by Calculation Method Used

Correlations

			Mean(OC Success)
Kendall's tau_b	Mean(OC Success)	Correlation Coefficient	--
		Sig. (2-tailed)	.
		N	125
	D(Pixel Proximity)	Correlation Coefficient	.669**
		Sig. (2-tailed)	<.001
		N	124
	D(replication)	Correlation Coefficient	.682**
		Sig. (2-tailed)	<.001
		N	124
Spearman's rho	Mean(OC Success)	Correlation Coefficient	--
		Sig. (2-tailed)	.
		N	125
	D(Pixel Proximity)	Correlation Coefficient	.813**
		Sig. (2-tailed)	<.001
		N	124
	D(replication)	Correlation Coefficient	.853**
		Sig. (2-tailed)	<.001
		N	124

**. Correlation is significant at the 0.01 level (2-tailed).

Table 18 contains a nonparametric correlational assessment of predictor and criterion variables using Kendall's Tau and Spearman's rho analyses. Both the Kendall's Tau and Spearman's rho tests are used to measure the correlative strength of bivariate association between predictor and criterion variables and are robust against non-normality and heteroskedasticity (Minitab Express Support, n.d.). Warner (2012) advised that when scores are derived from ordinal data, Spearman's rho or Kendall's tau are appropriate for the assessment of correlative strength. Using the Kendall's tau statistic, the correlation coefficient between OC success and fractal dimensionality when calculated using the pixel proximity method was 0.67 ($P < 0.001$). The Kendall's tau for FD when measured by replication method and OC success and was 0.68 ($P < 0.001$). The Spearman's rho correlation between predictor and criterion variables was 0.81 ($P < 0.001$) and 0.85 ($P < 0.001$) for the D(Pixel Proximity) and D(replication), respectively. Therefore, both the parametric and nonparametric measures of association consistently demonstrated a strong correlation between FD and OC success despite the nonparametric and heteroskedastic nature of the results.

Because the correlation coefficient from all three correlation testing methods indicated that there was a linear relationship between FD and OC success, a final verification of my research required that I plot the relationship between predictor and criterion variables (see Figure 18). Fractal dimension when calculated by the pixel proximity method significantly predicted OC success, $B= 20.651$, $t(122)=12.651$, $p<0.01$. Fractal dimension also explained a significant proportion of variance in OC success scores, $R^2= 0.564$, $F(1, 122) = 160.05$, $p<0.01$. The regression equation (Appendix E) showed that each unit increase in $FD_{\text{pixel proximity}}$ score was associated with an increase in mean success score by 20.65 Likert-scale points. The Y-intercept value was negative but is relatively meaningless because the FD calculation cannot be below a value of 1. The residuals from the regression did not show any significant patterning vs. run order and the residuals histogram showed that the residuals appeared to be normally distributed. The regression plot in Figure 18 and in the residuals vs. fit plot in Figure 19 show that there was an apparent sensitivity to variation for low success or FD scores, presumably because success levels close to zero are difficult to distinguish in a pixel-based measure of misalignment, or perhaps there might be little separation in the measurement scale at extremely low levels of success or alignment.

Figure 18

Regression Plot of OC Success as the Dependent Variable and FD$_{pixel\ proximity}$ as the Independent Variable

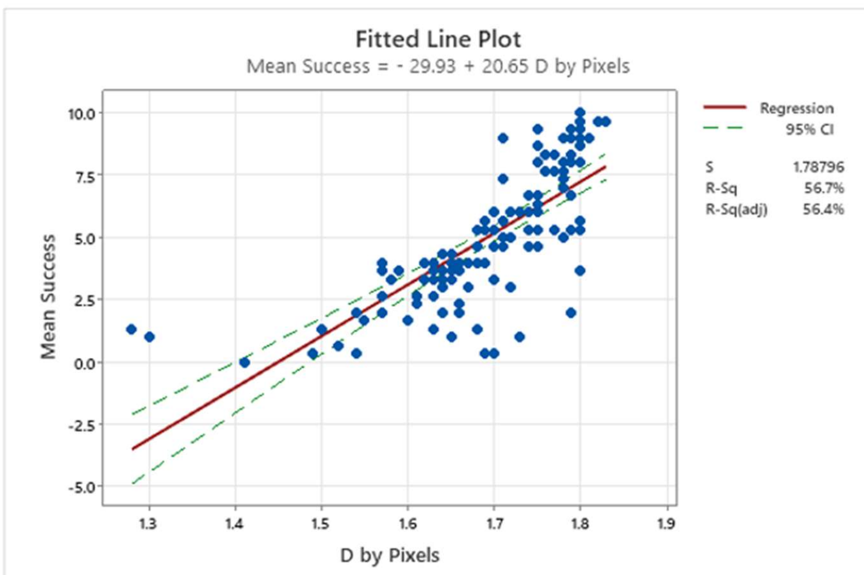
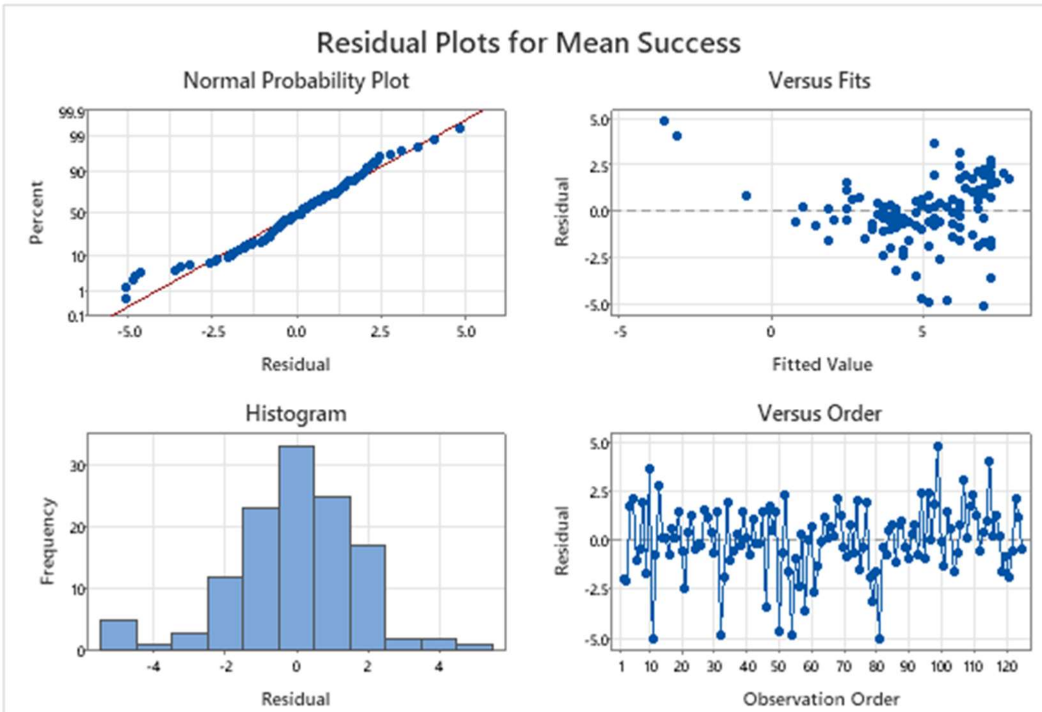


Figure 19

Residuals Plots of OC Success as the Dependent variable and $FD_{pixel\ proximity}$ as the Independent Variable



I repeated the regression analysis using OC success as the dependent variable and $FD_{replication}$ method. Appendix F contains the specific statistical tables from the analysis. The regression curve (see Figure 20) showed a general linear fit for the FD when using replication method. In this case, Fractal dimension significantly predicted OC success, $\beta = 0.785$, $t(122)=13.982$, $p<0.01$. The linear regression also explained a significant proportion of variance in OC success scores, $R^2= 0.613$, $F(1, 122) = 195.483$, $p<0.01$.The residuals plots (see Figure 21) showed the same general normality and sensitivity noted for the $FD_{pixel\ proximity}$ method. I infer from these results that the regression model fit the success scores a little better using replication when compared to pixel dimension.

Figure 20

Regression Plot of OC Success as the Dependent Variable and $FD_{replication}$ as the Independent Variable

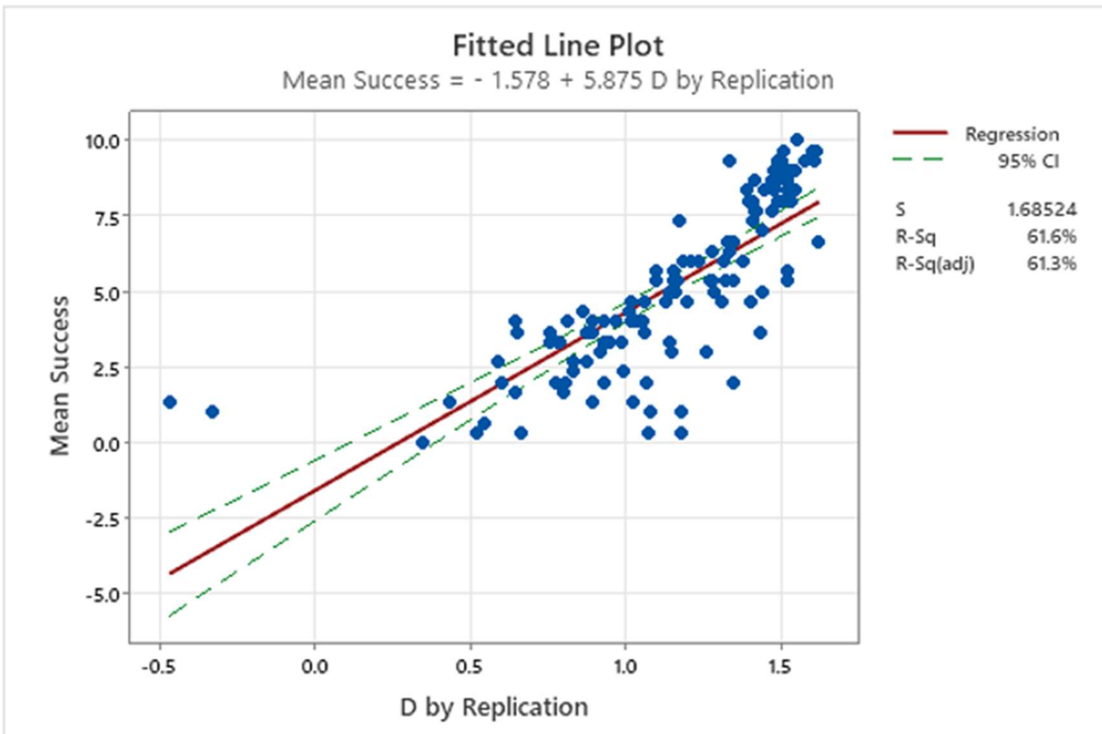
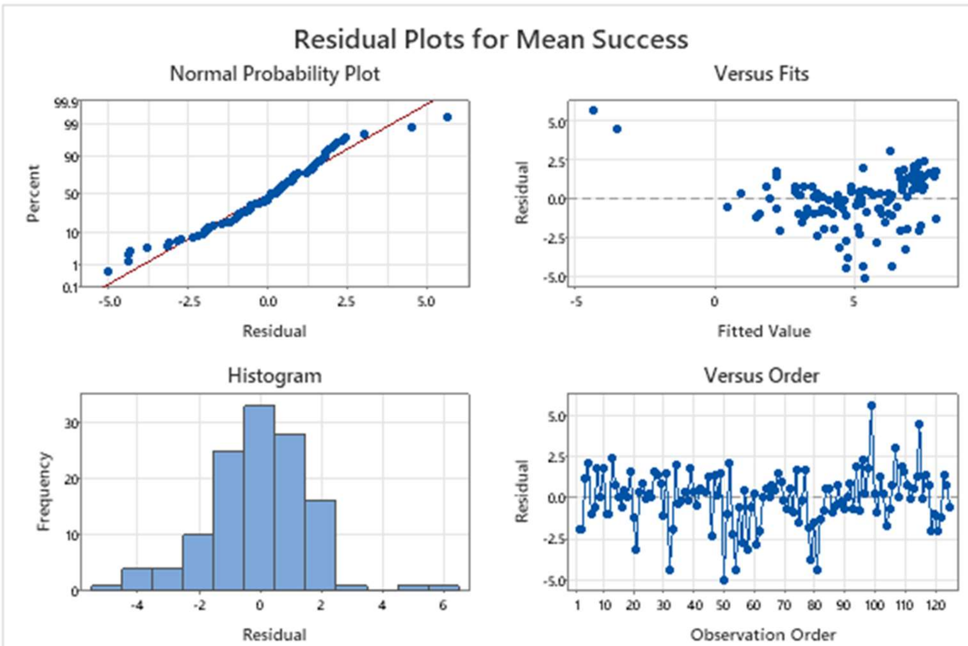


Figure 21

Residuals Plots of OC Success as the Dependent Variable and $FD_{replication}$ as the Independent Variable



Although not displayed in the regression figures, the collinearity condition index for both regressions were below 30, indicating that collinearity was not an issue for either regression (IBM, 2021a). I did not require a Bonferroni correction for my regression analysis because I only compared two variables (Laerd Statistics, n.d.).

The P-values for the regression fits in the ANOVA tables for both FD calculations were below 0.05 and indicated the regression results were statistically significant at the 95% confidence level. The Durbin-Watson statistic from both regressions were slightly below 2, showing a slight positive autocorrelation effect; however, the values were within the acceptable limits for survey analysis (see Kenton, 2021; M. L. King, 1981). The

ANOVA tables (see Appendices E and F) from the regressions indicated that the regression models had sufficient resolving power, and the F values of 160 and 195 for pixel method and proximity methods, respectively, indicated that the between-factor variation was larger than the within-factor variation. Because the significance of the F-statistics was less than 0.05. The variable inflation factor (VIF) for both regression fits were well below the value of 1.5 typically used as the rule-of-thumb for identifying collinearity issues with the regression (Allison, 1999). Therefore, I concluded that either FD method for calculating resulted in a statistically significant correlation between FD and OC success.

Conclusions

In this chapter, I discussed the data collection process and results. This study used a sufficiently large sample size, as determined by three different measures of sample size calculation methods for thematic and correlative significance. Although I was only able to use 125 of the responses after cleaning and screening, I had sufficient sample size for my analysis. My sample demographics were consistent with published aerospace demographics. However, my demographic breakdown of gender revealed a slight overrepresentation of female contributors. Most of the survey participants for the study were recruited from LinkedIn.

I also discussed the process used to screen and clean the data and justified my decision to leave blank values uncorrected because they did not benefit significantly from multiple imputation substitution. I also described my retrospective CFA and IA process to check the internal consistency of my survey. I concluded that my results were consistent with the two validated surveys from which the survey was created.

Before I could answer my research question, I first had to calculate the fractal dimension for each survey response. I described both methods used to calculate fractal dimension and the differences between the two methods. With two measures of fractal dimension and a comprehensive success score, I was able to determine the strength of association between OC success as a criterion variable and fractal dimension as a predictor variable. Using a bivariate Pearson's correlation, I determined that there was a strong correlation between predictor and criterion variables; however, the non-normality and heteroscedasticity of the data led me to verify the association using Kendall's Tau and Spearman's rho assessments of correlative association. All three methods consistently demonstrated a strong positive correlation between OC success and FD, regardless of the method used to calculate dimensionality. I demonstrated the positive association between FD as an independent variable and OC success as a dependent variable by plotting their linear regression relationships. The resultant regressions were not perfect; however, the linear fit accounted for approximately 60% of the observed variation.

Upon consideration of all the evidence, I believe there was sufficient evidence to reject the null hypothesis in my research question and accept the alternate hypothesis. I concluded that there was a quantifiable link between the degree of organizational alignment during OC and its success. Specifically, I concluded that there was a significant positively correlated association between fractal dimension and organizational success at the 95% level of confidence. The regression fits for both FD calculation methods resulted in a statistically significant fit for OC success; however, neither regression model explained more than 56% of the observed variation. Therefore, I also concluded that neither regression curve should be generalized beyond the current study without additional test.

Summary

In Chapter 4, sampling, data collection, and data analysis were discussed. Although 185 people responded to my solicitation to participate in the survey, only 155 people accepted the implied consent decree and were granted access to the instrument. Of the 155 remaining volunteers, I was able to use 125 surveys after data screening and cleaning. I provided my rationale and process for data cleaning and screening as well as the validation of the research instrument using CFA and FA. The responses to the fractal emergence survey were internally consistent and appeared to be consistent with the results from the original source surveys. My rationale for leaving missing response data blank in the analyses were presented and defended. I also described the methods used to calculate fractal dimension and my interpretation of the results. My research question was answered, demonstrating a strong association between fractal dimension and organizational success. The null hypothesis, H_0, for RQ1 was rejected. It appears that the link between dimensionality and OC success is plausible. In the next chapter, I will present the implications and limitations of my findings and describes potential areas for future studies.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative study was to determine whether fractal patterns of self-similarity and self-replication were present and measurable in the OC process. My research question addressed whether there was a quantifiable association between fractal dimensionality across an organizational hierarchy and OC success. In Chapter 4, I discussed the details of my data collection and data screening and cleaning processes. I described how I calculated the FD across the organizational hierarchy and presented the results using two different dimensional calculation methods. Both methods yielded similar results and allowed me to answer my research question. My research question addressed whether SOFT applied to managed human systems such as aerospace organizations that had undergone an attempt to change some aspect of their behavior. I tested the null hypothesis of my research question and rejected the notion that there was not a statistically significant association between FD and OC success. Both the parametric and nonparametric analyses of correlation confirmed the positive association between fractal dimensionality and change success to a 95% level of confidence. I demonstrated the association between FD and OC success by plotting a regression of OC success as a function of dimension. However, due to its limited validity, the regression curve could not be used to generalize OC success beyond a proof of concept.

The benefit of this study was that it demonstrated that seemingly intractable concepts such as OC quality can be measured in a complex system using fundamental physical science concepts such as SOFT. My research was novel in examining whether fractal mathematics could be applied to management research. In answering my research question, I proposed that extensions of this work could lead to real-time measures of OC success and that the fractal approach could be applied to other management science topics

In this chapter, I discuss and interpret my findings. I also discuss some of the limitations of my findings and how they impacted the generalizability of my conclusions. I reflect on how my research could be extended and enhanced, and I make recommendations for follow-up research. Lastly, I discuss the implications of my research and describe how my results contribute to positive social and organizational change.

Interpretation of the Findings

I designed my study to address the lack of quantitative links between organizational alignment and OC success. I posited that a quantitative measure of OC would allow organizational leaders to proactively assess change success and to understand and better manage change efforts. Marshak and Bushe (2022) found that without diagnostic measures, organizations have little ability to alter their management practices or course during an OC. The use of a FD provided a relatively simple way to assess OC alignment. My findings could be the gateway to future research that leads to a real-time measure of OC success.

In the literature review, I summarized the preponderance of published research to indicate that fractal properties were measurable in OC. Based on the scholarly support for the premise, I proposed that the research would be able to (a) show evidence for self-scaling behavior expressed using a FD, (b) demonstrate a measurable FD from fractal emergence survey responses, (c) show that the dimensional factors correlated with the outcome success for the OC initiatives described by the participants, and (d) simplify the characterization of alignment using a FD measure. I interpret the findings from this study to be a confirmation of each of these goals. This means that SOFT is a satisfactory conceptual framework for describing a changing organization by its degree of self-similarity across its organizational hierarchy. This reinforces the conclusions of other researchers who proposed that complexity could be characterized from the standpoint of scale and dimension (Y. Chen & Long, 2021; Tao, 2017).

The study confirms several of the qualitative studies I described in my literature review that hypothesized fractal behavior in organizational activities. Because there was strong statistical evidence that allowed me to reject my study's null hypothesis, I interpret my findings to confirm that self-replicating and self-scaling beliefs and behaviors are indicators of OC success. Because the correlations between my predictor and criterion variables were reasonably large and the regression curves were positive, I concluded that as hierarchical alignment increased, so does FD. Because the FD was an indicator of self-replicating behavior, I also inferred that higher degrees of self-replication were associated with higher degrees of OC success.

Because I was able to answer my research question, I interpreted the results to indicate that the collective outcomes of emergent individual levels are present as fractal properties across and within the organizational hierarchy. This view was consistent with Weber's (2019) study on information flow in multiplicative ergodic systems that view information as a vector-based consequence of its location within a social network.

Although Weber did not mention SOFT behavior in OC, Weber supported the notion that fractal self-replication should be present and measurable within a human system undergoing dynamic behavior.

My results are consistent with the sources in my literature review that hypothesized that fractal behaviors are present in human social systems such as aerospace companies. My work substantiates Malik’s (2015) premise that individual acts within an organization undergoing change can act as Mandelbrot seeds setting a recursive archetype that can be measured. The strong correlation between FD and OC success indicates that Kurakin’s (2011) SOFT is applicable in social research. SOFT theory addresses many of the persistent gaps in the scholarly OC literature by providing a deterministic method to quantify self-scaling change behaviors and attitudes during or after OC. My results demonstrate a proof of concept that Kurakin’s SOFT applies to OC.

Although Schowengerdt (2006) and H. Liu et al. (2020) proposed that fractal dimensionality could help simplify the measurement of complex system behavior, my study was the first of its kind to demonstrate quantitative support for the premise that the FD can be calculated and analyzed as a predictive factor in OC. My results extend H. Liu et al.’s depiction of noninteger intermediate fractal dimensionalities as means by which to find nonuniformities or irregularities in the organizational surface. In H. Liu et al.’s case, irregularities allowed the researchers to identify abnormalities in X-ray photos. In the current study, I demonstrated that FD calculated by pixel proximity could be used to express differences or irregularities in hierarchical alignment. Lower FD scores were related to lower OC success in an analogous way to H. Liu et al.’s depiction of lower pixel dimensionality indicating lower chances of benign tumors in an X-ray image. Both studies showed that the higher the FD, the higher the uniformity across scales.

Because my study confirmed that SOFT might apply to human systems undergoing change, I also interpreted my findings to indicate that it was likely that the three fundamental principles of SOFT also apply. Although testing for information flux was outside the scope of this work, my proof-of-concept study added credence to the sources in my literature review that described self-scaling flux as an analog of information flow. Because my FD measures captured the degree of alignment, it follows logically that lower FD scores represented entropic elements overcoming the organization's attempts to manage information flow and behavioral outcomes. This interpretation is consistent with Haken and Portugali's (2021) description of information flux as a type of energy characterized by flux and entropy principles. Even though my study did not prove Haken and Portugali's description of flux and entropy, I propose that my results did not countermand their premise.

Westbroek et al. (2020) described communication across organizational levels as a countermeasure to complexity whose effectiveness moderates the evolution of a system. In other words, successful change requires effective communication. I envision entropy in the context of OC as the tendency for change efforts to become disharmonious across organizational boundaries during a change process. My results indicated that a lack of alignment across boundaries was tied to lower OC success. In the physical sciences, entropy proceeds unless energy is supplied to promote order (Goekoop & de Kleijn, 2021). In an organizational context, management energy is needed to overcome entropy

(Heorhiadi et al., 2018). Lind and Sulek (1994) described dialectic or communication energy as a type of management energy expended to counterpoise entropy during a change. Communication and information flow are the mechanisms that promote organizational learning (Brandtner & Freiling, 2021) and adaptation to the desired behavior. My findings showed that lower alignment was related to lower OC success, which does not prove that information flux is entropic across a change; however, my results were consistent with the premise and could be used to support future research in the topic.

The concept that beliefs and behaviors are self-scaling flux supplements the work of Andrianova et al. (2020) and Silva and Guerrini (2018) who proposed that information exchange and learning are best characterized as an informational ebb and flow as individuals adapt to change. This extends Weber's (2019) description of change as an observable function of OC energy as dynamic interplay information sinks and sources as a self-scaling phenomenon. However, to fully analyze Weber's premise, additional studies are required.

When viewed in SOFT terms, information flux as a quantitative property in a changing system supports Lawrence and Botes's (2011) description of change as an autopoietic process. Lawrence and Botes proposed that OC success is based on an organization's ability to make self-scaling changes. I infer from my results that not only were Lawrence and Botes correct, but the notion of autopoiesis is an attempt to adjust composition to conserve its energy and manage flux imbalances across hierarchical boundaries. Malik (2015) described the organization as a fractal entity and proposed that information and actions are identifiable as a fractal enterprise. Joseph (2019) also speculated that adaptation to change is a fractal property within an organization. Because my study showed a statistically significant correlation and a positive regression of OC success as a function of fractal dimensionality, my study's findings reinforce Malik's work and quantitatively verify Joseph's premises. My study also helped explain Sander's (2017) observations that self-scaling behaviors were observable and reinforced the notion that self-scaling properties can be quantified. Although my study was exploratory, it supported Malik's proposition that OC was a fractal property.

The second tenant of SOFT is self-organization. I did not directly assess self-organization. My instrument measured individual responses and participants' expressed views of how adjacent hierarchies acted relative to an OC. However, I did measure concepts that are related to self-organization. Because my instrument was a fusion of Li et al.'s (2016) resistance to change and Ai et al.'s (2019) creolization surveys, I interpret my results to indicate that the resultant FD value for a given organization represented the alignment of beliefs (creolization) and behavioral intent (resistance to change). Kurakin (2011) proposed that observable macroscopic order was nonlinear across the system superstructure, and the return to stability required a cooperative sequence of actions across domain boundaries. In the current study, domain boundaries could be interpreted as organizational levels, and stability could be construed as each level self-organizing in a way that is consistent with OC success. Therefore, I interpret that my FD calculation indirectly assessed the level of self-organization across the enterprise. Like the first tenet of SOFT, my study supported the notion of self-organization and provided no evidence to the contrary. My results were consistent with the notion that self-organization and scale-invariant behaviors increases FD scores, thereby facilitating successful OC. I interpret my results to denote that self-organization is a synthesis of adaptation to the change through creolization and lowering resistance to change. However, to fully prove the second principle of SOFT would require additional study.

Haken and Portugali (2021) depicted information flow as a self-organizing property in a human social system. My study showed that beliefs and behaviors were positively correlated with OC success. In that regard, my study confirmed Haken and Portugali's (2021) description of self-organization as the alignment of actions and beliefs in a complex adaptive system as a means by which to seek balance through the establishment of new norms. My study findings indicated that all levels of an organization behaved and align uniquely during the change process. Almost none of the survey respondents described creolization or change resistance as uniform values across the hierarchy. Instead, participants tended to score beliefs and behaviors consistently as positive or negative with different magnitude values. Those with generally positive scores also showed higher FD and were associated with higher OC success rates. If I interpret this in the context provided by Botev (2020), the individual differences in alignment scores for different level dyads show that different hierarchical levels adapt to change based on their circumstances and needs. I consider it illogical to assume that all levels would organize the same way and at the same pace. I argue this behavior is present in my data set and indicated the presence of self-organization without specifically proving it.

The third fundamental principle of SOFT is that the degree of complexity and order within a self-organizing nonequilibrium system is characterized by the rate of energy/matter passing through the system (Kurakin, 2011). A live study of an OC would be needed to confirm the dynamic nature of information and belief flow across a changing organization. Because I did not track an organization under change, I did not supplement the work of Ben-Menahem et al. (2013) who characterized OC as a system that seeks equilibrium through self-organization. However, because my instrument was capable of measuring alignment of beliefs and behaviors, I infer that it could be used to study the rates of change across a system amid change were it to be applied during a live change process. More work would be needed to design and run a real-time study of change; however, my interpretation of the fractal emergence study results is that adding a temporal factor to the study would allow for the measure of dynamics during change and could support Ruben and Gigliotti's (2021) premise that information acts in terms of energy.

Research Question

My research question addressed whether OC success was correlated by the degree of self-similarity and self-replication across hierarchical boundaries during a formal change effort. I sought to ascertain whether there was a correlation between measured FD and expressed OC success:

RQ: Is there an association between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success?

H_0: There is no correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

H_a: There is a statistically significant correlation between the FD of alignment of OC beliefs and behavioral intentions across an organizational hierarchy and OC success to a 95% degree of statistical confidence.

The null hypothesis, H_0, was rejected for the research question in one parametric and two nonparametric correlation tests and using either measure of FD. Using the Pearson's product-moment correlation test, the FD, calculated using the replication method, demonstrated a strong association between the replication construct of dimension and OC success, with a value of $r = 0.785$, $p < 0.001$. When FD was measured using the pixel proximity method the Pearson's correlation decreased slightly to $r = 0.768$, $p < 0.001$.

However, with normality and homoscedasticity in question, I also evaluated the correlations using Kendall's tau and Spearman's rho methods, which were less sensitive to the normality of the variables. The results from both nonparametric methods were consistent with the Pearson's correlation outcomes. I concluded that the correlation between the FD calculated using the replication method demonstrated a strong association between the $FD_{replication}$ method and OC success, with a value of $r = 0.682$, $p < 0.001$ for Kendall's tau, and $r = 0.853$, $p < 0.001$ for Spearman's rho. The correlation between the FD calculated using the pixel proximity method demonstrated a strong association between the FD_{pixel} method and OC success, with a value of $r = 0.669$, $p < 0.001$ for Kendall's tau, and $r = 0.813$, $p < 0.001$ for Spearman's rho.

Because all methods used to calculate dimension and all methods used to interpret the relationship between the fractal dimension and OC success resulted in consistent, positive correlations above 0.6, I concluded that the FD was a quantitative indicator of OC success.

I the previous chapter, I described several statistical issues with the dataset that prevented me from declaring a perfect link between fractal dimension and organizational change success. Missing data, lack of a definitive CFA result, and the non-normality of the predictor and criteria variables all obfuscated the relatively strong correlative ties between hierarchical alignment expressed as FD and the resulting OC change success. Adding to the uncertainty in the conclusivity of the results were the heteroscedasticity of the correlations across the entire scale. I interpreted the uncertainty to indicate that there is still more research work needed in the area of fractal mathematics as applied to organizational change studies. However, when reviewed as a whole, there was a consistent positive association between fractal dimension and success. I believe the overall consistency of the findings in aggregate satisfied my goal to prove the concept of SOFT as a framework for evaluating OC.

Although my results proved that fractal mathematics could be applied to OC research, several irregularities in the dataset and the analysis results were present in the study. For example, the unusual data points at low FD scores in the regression curve need to be better understood before this study can be generalized beyond the sample population. The regression curve predicting success as a function of FD should be considered specious beyond its use to verify that the relationship between OC success and FD was generally positive.

Choosing Between the Two FD Calculation Methods

Although not explicitly one of my stated research goals, I was curious about which FD calculation method was a better as a method by which to describe or predict OC success. The correlation values associated with the FD replication method led me to infer that FD by replication was a better predictor of organizational success than the FD by the pixel proximity method. Table 19 shows that the FD by replication method yielded between 2% and 5% higher correlative strength than the FD by pixel proximity method.

Table 19

Comparison of Correlative Strengths Using Either FD Calculation Method

Because the two methods used to calculate dimensionality measures were intended to characterize the fractal dimension based on similar principles, I anticipated a high degree of collinearity between the two fractal dimension calculation methods. The matrix plot in Figure 22 shows a distinct association between the two FD calculation methods. There was a strong Spearman's rank correlation between the two calculation methods $r(2) = 0.936$, $p < 0.01$ (Table 20).

Table 20

Pairwise Spearman Correlation between $FD_{Pixel\ Proximity}$ and $FD_{Replication}$

Pairwise Spearman Correlations

Sample 1	Sample 2	N	Correlation	95% CI for ρ	P-Value
FDPixels	FDrepl	124	0.936	(0.904, 0.958)	< .001

Because both methods satisfactorily correlated with OC success, one possible interpretation was that either method is satisfactory as a predictor of OC success. However, to determine which method was a more reliable predictor of OC success, I compared the two methods using a stepwise regression with OC success as the dependent variable to obviate the collinearity between the two FD calculations. I used the default stepwise selection criteria of P(F-to-enter) <= 0.050 and P(F to remove) >0.10.

Table 21 shows the resulting stepwise regression model summary with the $FD_{replication}$ selected and $FD_{pixel\ proximity}$ excluded from the regression. Based on these results, I concluded that both fractal dimension methods were valid, but that the calculation of FD by replication was slightly better than the calculation of FD by pixel proximity at predicting OC success.

Table 21

Model Summary of Stepwise Regression Showing Exclusion of FD by Pixel Proximity

Model Summary[b]

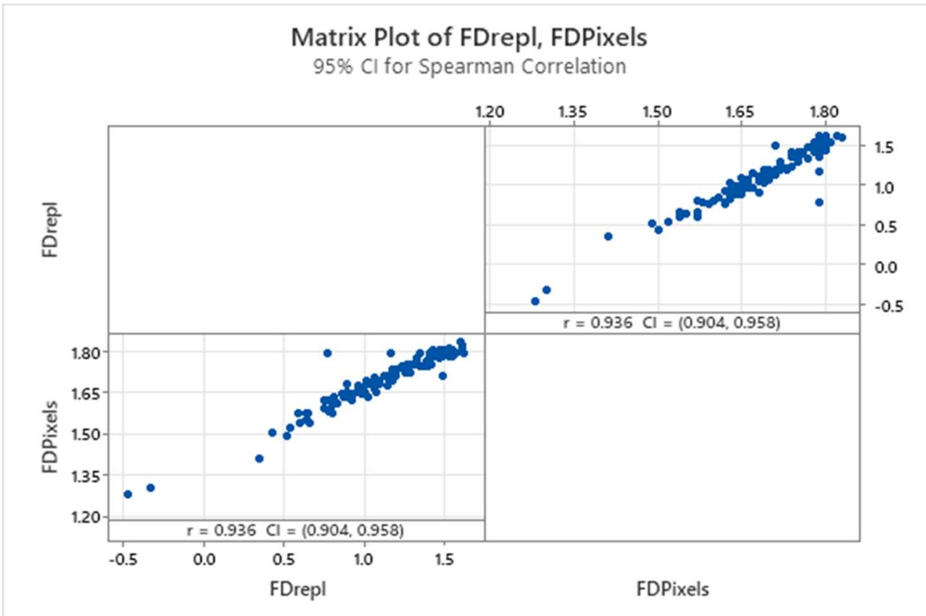
					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.819[a]	.671	.669	1.55131	.671	249.119	1	122	<.001	1.831

a. Predictors: (Constant), DbyReplication

b. Dependent Variable: Avesuccess

Figure 22

Matrix Plot of FD Measured by Pixel Proximity and Replication for the Data Set

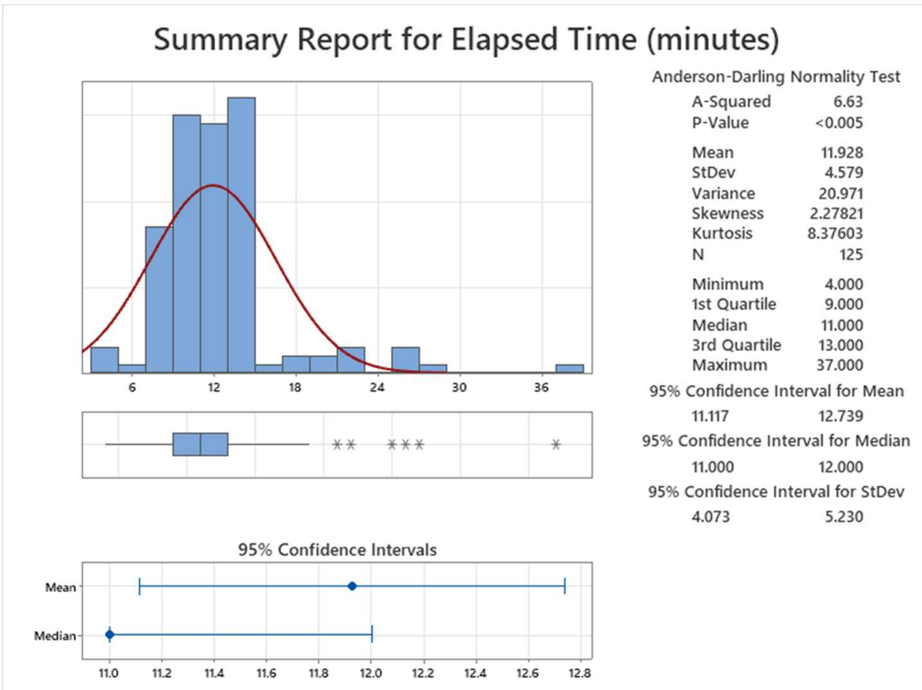


Limitations of the Study

I anticipated and discussed several threats to the validity of my work in Chapter 3. However, after analyzing my results, I am confident that I successfully answered my research question. Still, there are several limitations in this study that threaten the overall generalizability of my results.

Figure 23

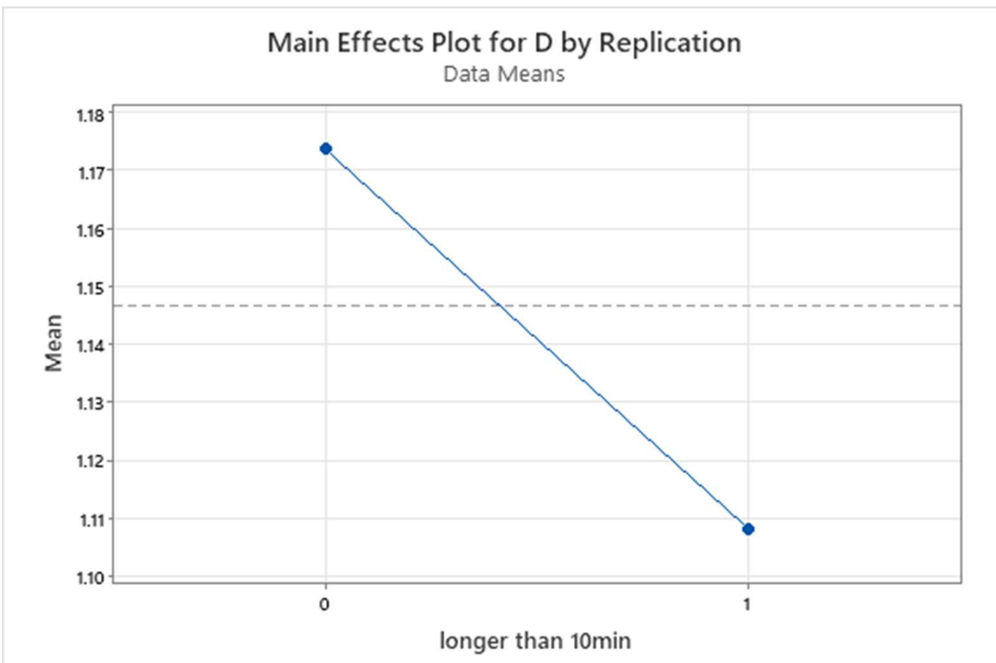
Summary Report of Response Times for Valid Surveys



As I discussed in Chapter 3, I was concerned that maturation bias might make participants less attentive to their answers at the end of the survey than they were at the beginning of the survey due to the passage of time (see Onwuegbuzie, 2000). One of the limitations of my survey instrument was that it was rather lengthy, with 48 questions. I had anticipated that the survey might take as long as 30 minutes or more to complete. However, according to the timestamps for valid responses based on their start and end times (see Figure 23), the mean value for the survey completion time was 12 minutes (SD = 4.6). Although the survey completion time was shorter than I anticipated, the maximum length was 37 minutes. Kost and da Rosa (2018) found that surveys exceeding ten minutes were associated with lower retest reliability compared with surveys taking less than six minutes. Chudoba (n.d.) cautioned that survey participants tended to spend less time reading and responding to individual questions on surveys when there were more than 10 questions total. Chudoba claimed that survey reliability suffered when surveys exceeded 15 minutes in length.

Figure 24

Mean Value of D by Replication as a Function of Time Spent Taking the Survey

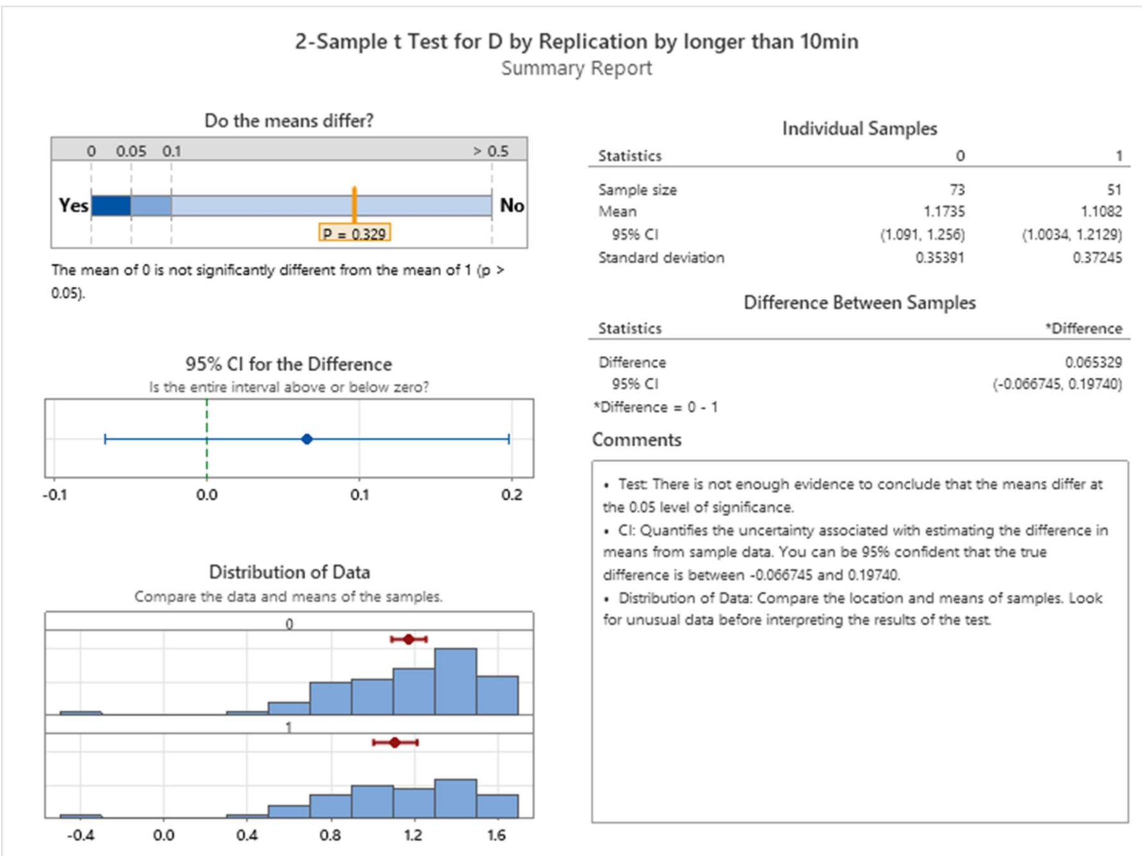


Although I could not directly control for maturation bias in my data, I was able to plot the mean value of D associated with respondents who spent more than ten minutes taking the survey compared to the mean D value for respondents who spent ten minutes or less on the survey. Figure 24 shows that the average $FD_{Replication}$ value calculated for those who spent longer than ten minutes completing the survey was approximately 0.07

lower than those who spent less time completing the survey. However, a Welch's 2-sample T-test indicated that there was not enough evidence to conclusively state that the difference between the responses was statistically significant (Figure 25). Welch's method was appropriate in this case because it is not sensitive to equal variance or normality when the sample sizes in each group are greater than 15 (see Wilcox, 2022).

Figure 25

2-sample T-Test of D by Replication as a Function of People Who Spent More or Less Than 10 Minutes Responding to the Survey

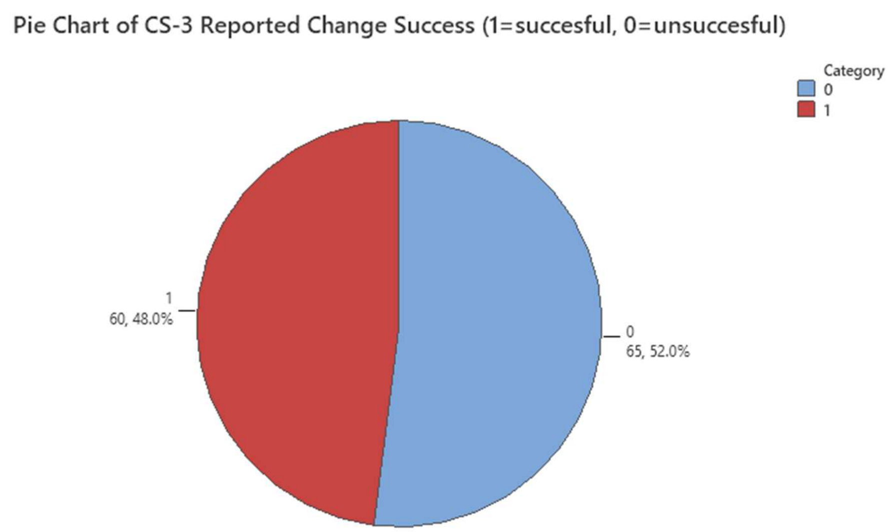


Despite the lack of specific evidence to indicate that maturation bias was present in my survey, it remains a threat to my results' overall validity and generalizability. Later in this chapter, I discuss recommendations to reduce the overall length of the fractal emergence survey.

Another limitation of my study was a slight demographic overrepresentation of female respondents in my study. There were 6% more female participants in my survey than reported for the general aerospace population. I infer from the overall internal consistency of my survey results and high correlation coefficients that my conclusions were unlikely to be impacted by a slight overrepresentation of females. Therefore, I do not conclude that the demographic overrepresentation of females in my study limited my interpretation of the study results. However, the general demographic makeup of the aerospace industry overall is significantly different than that of the overall population of North America. The lack of cultural diversity in the overall aerospace community is a limitation in my study and affects the generalizability of my conclusions beyond the aerospace population without additional research. For example, the United Nations demographic study for North America (United Nations Department of Economic and Social Affairs, Population Division, 2020) reported that slightly over 50% of the North American population was female, compared to approximately 25% of females in the North American aerospace community. The United Nations report also indicated that the median age of the North American population was 38.5 years, compared to a median age of 44 years in my study. Overall, the North American aerospace community at the time of my study was male-dominated, older, and had disproportionally higher levels of education (see Pold & Ivie, 2019) compared to the rest of North America. The demographic distribution of North American aerospace workers provided an inherent select bias in my results that prevents the generalizability of my findings to other industries without additional study.

Figure 26

Reported OC Success by Survey Participants



Another limitation to my study was the presence of an apparent self-selection bias. My recruitment method relied on self-selection of volunteers to participate in the survey. Given that almost two-thirds of reported organizational change processes fail (D. King & Land, 2018), I expected to see a higher proportion of unsuccessful change processes reported. Figure 26 shows the self-reported OC success variable CS3 collected as part of my survey dataset. Close to half of the respondents reported successful change processes in my study, which was significantly higher than the reported industry OC success rate. I did not ask the participants to select the most recent or most typical change experience and the volunteers were free to report on a successful or unsuccessful change. The participants in my study chose a relatively even split between the success and failure, which led to an overrepresentation of successful outcomes compared to typical OC outcomes. I infer that the participants who self-selected to describe the OC process in their survey were likely motivated by their attitudes regarding the intent of the survey or their desire to describe a specific change process, presenting a self-selection bias in the survey results (see Leedy & Ormrod, 2010). Therefore, I cannot claim that my results are generalizable to the typical OC outcome without additional research.

Because my survey had elements relating to alignment and success on an 11-point Likert-like scale, the responses to each question related to the participants' perception of success. I anticipated that the response data would not be normally distributed and expected that the global distribution of variables across a success to failure spectrum would be relatively flat. In retrospect, it was not surprising that many of my calculations required nonparametric analyses. My use of nonparametric analyses such as Spearman's rho provided me the ability to assess the results without requiring normality of the data. However, nonparametric analyses have less statistical power to detect differences in the population if they are present (Whitley & Ball, 2002). If I had a very small sample size or if my data showed weak correlations, the use of a nonparametric test would be concerning. I addressed some of the controllable aspects of nonparametric data in my research design by ensuring that I obtained a large sample size with sufficient statistical power from a reliable sample group. I further improved my statistical conclusivity by using two reliable instruments with prevalidated constructs. I am confident that my results were reliable because the Pearson's product-moment correlation agreed with the nonparametric Kendall's tau and Spearman's rho methods, and both FD calculation methods demonstrated a satisfactory regression fit to OC success. However, because my regression fit approximately 50-60% of the data, there is still some variation that remains unexplained by my analyses, and there are still some statistical conclusivity concerns that limit the generalizability of my results beyond the study sample.

Another threat to the validity of my research was my treatment of non-responses. I discussed how I handled the nonresponses within my dataset in Chapter 4. However, there was also a threat to validity from the nonresponses by people who chose not to participate in the survey (Appelbaum et al., 2019). A representative sample size helped ameliorate some of the research risks of non-response (Rose & Fraser, 2008). However, the generalizability of my results was limited to those who voluntarily responded. For my results to be generalizable, there must be no difference between those willing to participate and those who were not. Based on my research design and method for soliciting volunteers, I cannot know what the non-respondent population would have answered (Creswell & Creswell, 2017).

Another limitation of my study became apparent as I began calculating the fractal dimension using the Pixel method. Each response to the survey was limited by the hierarchical level of the respondent. The respondent was asked to discuss how workers, managers, and executives responded. The response created an (X,Y) dyad where the X value indicated the level of the respondent, and the Y value referred to the level the group the respondent described. Because there was not a matching pair of responses from the group in question (Y), there was no reflectivity in the calculation. For example, if a worker commented on how an executive acted or felt during a specific change, there was not a matching response for how that executive viewed the dyadic relationship. For my proof-of-concept study, a paired response was not needed. However, a better estimate of FD as an indicator could be made with a paired match for each response. Referring to the pixel maps shown in Figure 13 or those shown in Appendix D, the lack of dyadic pairs of data left the interactive pixel grids half-filled. In spite of this limitation, I was able to show a strong association between perceived alignment and perceived OC success. However, a corresponding (Y,X) association are needed to be completely confident in my results. Therefore, my study results contain an unquantifiable risk that self-reinforcing belief by an individual respondent might influence the respondents' objectivity in answering about how other groups performed. For example, suppose a worker felt that workers and managers were not aligned. In that case, a corresponding response from the worker's manager in the same organization and in reference to the same OC project would be required to estimate bias. Although I did not observe any evidence regarding a participant's objectivity based on the aggregate responses, without a corresponding paired assessment from the same group in the same organization, I cannot rule out bias as a threat to validity.

I discussed additional threats to the validity in Chapter 4. A general threat to the generalizability of my findings was the specter of statistical bias. My correlation testing was limited by heteroscedasticity and non-normality of results. My CFA demonstrated a lack of overall fit but revealed a good fit to the specific correlations and covariances. The factor analysis and item analysis supported the general conclusions from the CFA. I inferred that the overall consistency of the factor analyses demonstrated that the survey was valid and internally consistent with the original parent survey themes. However, the unequal variances noted in the Pearson's bivariate correlation were concerning and limit the generalizability of my results beyond this study. I am confident that the consistency in the association between FD and OC success as calculated by two different FD methods and tested using three bivariate correlation techniques verified the conclusions of my study. However, without additional testing and further development of the instrument to protect against statistical bias, further research is needed to develop and prove a SOFT-based fractal emergence model.

The final limitation of my research was that it demonstrated an association between FD and OC success, rather than proved a causal link between FD and OC success. A fundamental tenet of self-organizing-fractal theory is that it applies to all established complex systems and does not need to understand the motivations or drivers in the system to be modeled mathematically (Kurakin, 2011). A shortcoming of the FD approach is that understanding the drivers or motivations of the people working within a changing organization are required to refine the variables that are causally linked to OC success. I believe that I demonstrated a positive correlation between FD based on organizational alignment of OC beliefs and behaviors and the resulting change success. However, I have not demonstrated that alignment causes success, nor that success causes alignment. My study was limited to association, and further quantitative and qualitative testing are required to explore or test for causality. Because my approach did not include underlying qualitative information about why people act the way they do during change, I suspect that mixed-method research would be needed to supplement a causal inquiry.

Recommendations

In planning for this study, I proposed that if I could not find a suitable statistical test for correlation or regression, I would use a classification and regression tree (CART) to assess the associative relationship between the predictor and criterion variables. Because I was able to find a satisfactory statistical relationship, a CART analysis was not needed to assess my research question. However, one of the limitations of my survey related to its length. I recommend that some of the maturation bias present in my study could be reduced if the fractal emergence survey could be shortened. Given that my CFA and FA analyses showed good internal consistency, I was curious about which factors were least influential in the determination of fractal dimension and rationalized that I could use a CART analysis to identify which survey questions were the least impactful to in the FD measure.

Using Minitab's predictive analytics capability, I ran a CART analysis attempting to find an optimal tree design with the least absolute deviation using a 10-fold cross-validation model. My approach was similar to Gocheva-Ilieva et al.'s (2021) CART approach to finding important factors for student achievements and competencies in mathematics. My criterion variable for the evaluation was the $FD_{replication}$ because it had the highest overall correlation to success. I then used the creolization and resistance to change questions as predictor variables in the CART. The independent variables for the quantification of creolization were Identity multiplicity (IM), Cultural hybridity (CH), Boundary Spanning (BS), and Network Expansion (NE). The independent variables relating to resistive intent were loss aversion (LA), transactional costs (TC), social norms (SN), affective inertia (AI), behavioral inertia (BI), cognitive inertia (CI), and resistive intent (RI).

The CART method uses empirical pair comparisons of value changes given different independent variable and response combinations and identifies where certain factors drive large changes in the response value for FD (Johansson et al., 2022).

Figure 27

Mean Absolute Deviation vs. Number of Terminal Nodes

Response Information

Mean	StDev	Minimum	Q1	Median	Q3	Maximum
1.14664	0.361595	-0.469729	0.929281	1.17888	1.44044	1.62319

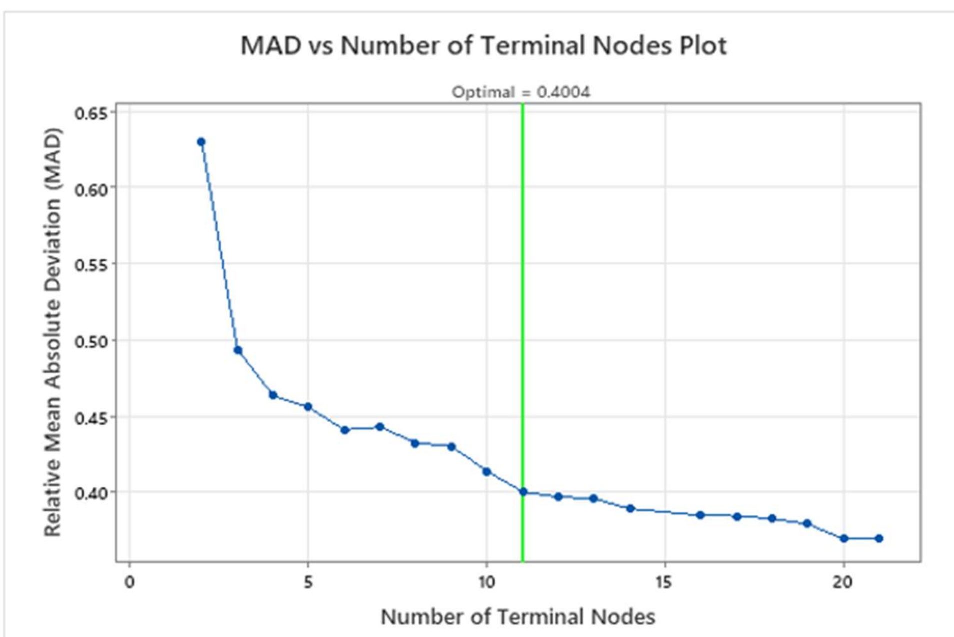


Figure 27 shows how the relative mean deviation (MAD) of the $FD_{replication}$ changed as a function of adding or removing independent variables. As factor combinations were added or subtracted, the highest MAD regarding a combination change was kept and compared to other combinations. If the MAD was higher, it was rejected, and another combination was sought until a mean vs. node diagram was made. In the mean absolute deviation analysis shown in Figure 27, the impact of adding additional terminal nodes decreased sharply and began to flatten out as new nodes were added. Based on impact to model deviation, the optimal number of nodes for thematic evaluation of FD was 11.

Table 22

Model Summary of Optimal CART Diagram

Model Summary

Total predictors	10
Important predictors	10
Number of terminal nodes	11
Minimum terminal node size	3

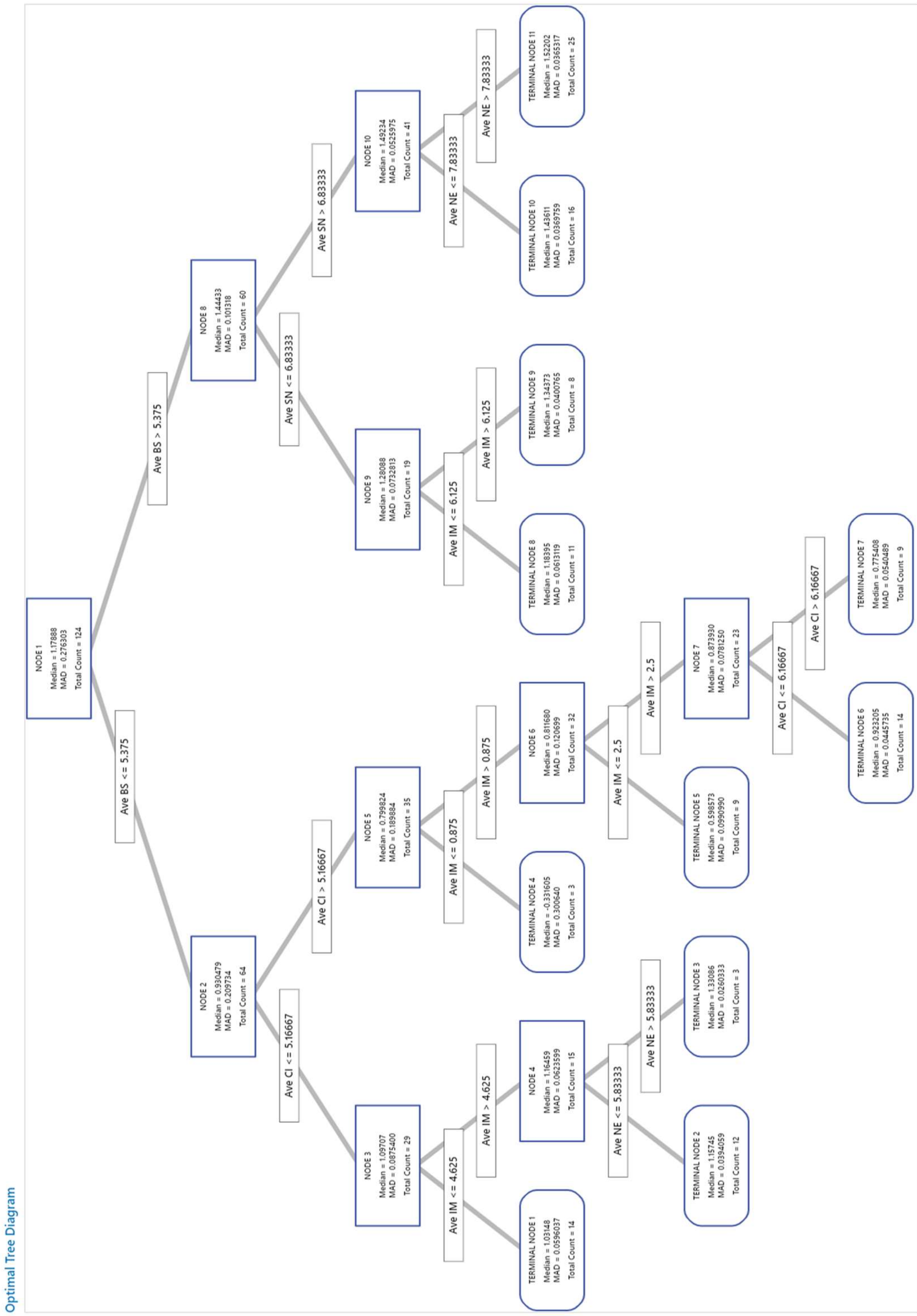
Statistics	Training	Test
R-squared	92.78%	72.06%
Root mean squared error (RMSE)	0.0968	0.1904
Mean squared error (MSE)	0.0094	0.0362
Mean absolute deviation (MAD)	0.0548	0.1106
Mean absolute percent error (MAPE)	0.0660	0.1479

The model summary for the classification and regression tree analysis is shown in Table 22. Like linear regression analysis, the R-squared value indicated the amount of variation explained by the model. The overall fit of the 11 node CART model was 72.06%, however, unlike linear regression models, the CART did not provide a p-value, and instead reported the mean absolute percent error. The mean absolute percent error was less than 1% in the 11-node model. Because the intent of the CART was to identify important factors in the fractal emergence survey and was not purposed to prove statistical correlation, I accepted the 11-node model. The nodes of factor-value combinations that significantly influence FD were displayed in an optimal tree diagram.

Figure 28 shows the mean absolute deviation (MAD) score for a given factor level based on significant deviation shifts in FD as the fractal emergence survey questions changed. Nodes occurred whenever the slope of the regression curve between the factors within the survey changed the MAD. The first node created based on boundary spanning. The CART model showed that FD was critically related to mean boundary spanning values above or below the value of 5.73; at that point, the median value of FD was 1.18. For values of BS > 5.74, the nodes split again based on social norms. For high levels of BS, and SN values above 6.8, the median value for FD was 1.44. The optimal tree continued to branch based on critical empirical values of the associations between FD and the selected factors.

Figure 28

Optimal CART Tree Diagram for the Factors in the Fractal Emergence Survey



From the model, the factors most influential on fractal dimension were determined and shown in Figure 29. The relative importance factor scores for each of the selected thematic factors was listed based on that factor's impact to the way $FD_{replication}$ changed at the value for the question changed in the survey responses. Average IM appeared to be most significant to the model, indicating that the model for FD improved the most when the value of identity multiplicity changed. Next were NE, BS, CI, SN, CH, and AF. The survey questions relating to TC, LA and RI comprised the bottom three thematic factors, with RI only contributing $< 10\%$ to $FD_{replication}$. Therefore, I recommend that resistive intent (RI) is a good thematic candidate to change or eliminate in future survey iterations.

Figure 29

Relative Importance of Factors Used in the Fractal Emergence

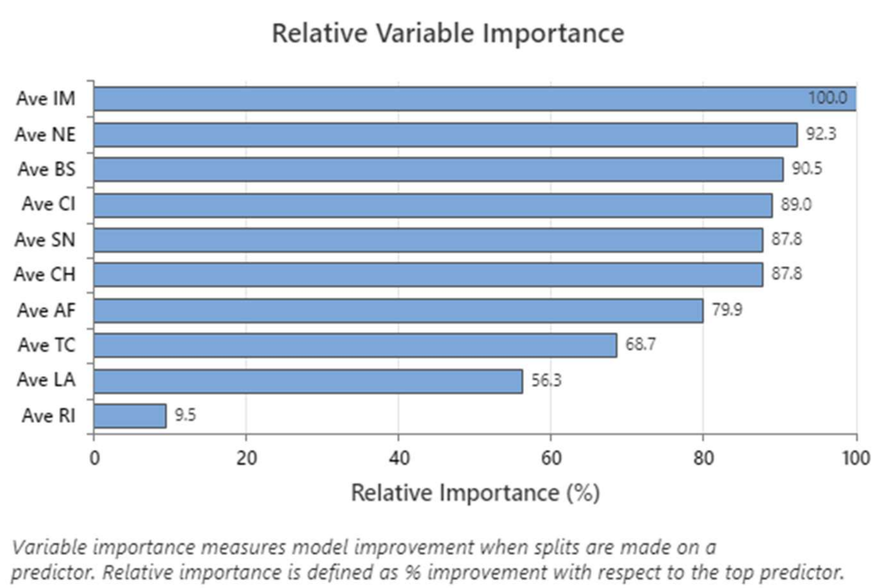


Table 23

Proposed Changes to the Fractal Dimension Survey to Improve (X,Y) Dyadic Measures

Proposed Changes to the Fractal Dimension Survey

Dimension or Category	Variable Name	Survey Question	Proposed change to improve FD measure and capture specific dyadic relationships
Affective Inertia	AF1	AF1 -I plan on using my pre-change method for getting work done or working with my teammates…because it would be stressful to change.	AF1 -I (prefer/preferred) working with my managers using the previous method instead of the new (changed) method
	AF2	AF2 - I plan on using my pre-change method for getting work done or working with my teammates…because I am comfortable doing so.	AF2 -I think managers and executives were more comfortable using the old method for getting work done instead of the new, changed method
Cognitive Inertia	CI2	CI2 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most efficient way of doing things	CI2 - I think workers and executives worked together more efficiently before the change
	CI3	CI3 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most effective way to do things.	CI3 -I think my colleagues worked more effectively with other workers before the change process occurred.
Resistive Intention	RI2	RI2 - I will fully cooperate/cooperated with the change to the new way of working.	RI2 -I think workers and executives are cooperating better as a result of the change
	RI3	RI3 - I intended/intend to comply with the change to the new way of working.	RI3 - I think workers and executives are working together better as a result of the change process.
	RI4	RI4 – I (did not /do not) think the change initiative is needed.	RI4 –I think executives and managers are working together better since the change process began

Another recommendation for future work exploring the nature of hierarchical alignment and fractal dimension is to adjust the survey questions to capture specific dyadic alignments. Because both the resistance to change and the creolization parts of the fractal emergence survey contained numerous questions about how an individual felt or behaved, the survey was very long and asked several similar questions about an individual's beliefs or behaviors. Redundancy was good for assessing reliability and essential for determining the (X, 1) dyadic values. However, not all the measures were needed to accurately assess mean individual values. For example, AF1 AF2 and AF3 asked very similar questions, and CI2 and CI3 were also redundant. The previous CART analysis showed that that RI1, RI2, RI3, and RI4 questions did not significantly contribute to the fractal dimension value and were good candidates for elimination. Rewriting several of the questions would have allowed a clearer assessment of the (X,Y) dyads because they could be changed to specifically address the specific dyadic relationship in question. Table 23 contains a set of recommended changes to the survey. Changing the survey would make it easier for the survey respondent to understand what was being asked. Rewriting the questions to specify the dyadic pairing would be less prone to misinterpretation (for example, to ask a worker about other workers instead of asking about colleagues), More importantly, asking questions about specific dyadic pairings would involve less conditional programming in the $FD_{replication}$ calculation to assess which hierarchical level a "colleague" referred to in the respondent's answers. With fewer logical programming steps, the probability of making a programming error in the $FD_{replication}$ would decrease. However, the changes to the survey would likely require a new factor analysis to revalidate the instrument.

Implications

This study helped support the notion that complex organizational behavior can be evaluated through self-replication and self-scaling fractal behavior. However, there is still much to be discovered about the nature of fractals within social research. My study was exploratory in nature, so its overall generalizability must be confirmed through follow-on research. My work helped reject the notions held by researchers like Hallencreutz and Turner (2011), who suggested that human organizational behavior within an organization were too complex to measure. Instead, this study provides at least an anecdotal proof of Nuhfer’s (2017) argument that human systems can be viewed through the theoretical lens provided by the physical sciences. Specifically, this work confirmed that self-organizing fractal theory appears to apply to complex human systems like the North American aerospace community.

Because there were several limitations to my study, my conclusions require further refinement and validation within the organizational change research community and across the field of social science in general. However, because my work demonstrated the first novel confirmation that fractal mathematics can measure organizational alignment during OC , it has implications for future research, practice, and positive social change.

Implications for Research

Eroshenko et al. (2019) proposed that the current models used in social science limited a researcher's ability to understand complex behavior because the old models built on previously accepted paradigms without improving their ability to deal with emerging complexity. Eroshenko et al. advocated for a synergistic blending of social science and the quantitative methods most commonly used in the physical sciences. Although I evaluated the association between fractal dimension OC success, SOFT remains largely unexplored in human organizations. As an exploratory study, I believe that I proved that fractals could be measured in organizational hierarchy and that FD was correlated with OC success. However, as a nascent approach, there is still much to accomplish before my research can be considered generalizable. The extension of my study to a more generalizable result represents an opportunity to expand fractal research in social science. Considering just my study follow-on research must expand the FD concept beyond my study group, perhaps evaluating if my results can be duplicated outside of an aerospace community. Second, as I described in the recommendations, researchers could improve my survey instrument by making it shorter and adding more specific dyadic measures. Third, researchers could expand the scope SOFT beyond OC into other areas of social research.

A goal of my research was to reduce the knowledge gap in extant organizational change literature using a quantitative study of fractal dimension and its relationship to OC success. An implication of this study relative to research is that it could foster additional studies to further explore the use of FD in social systems research. Additional research could explore the quantitative degree of hierarchical coordination and alignment during change, building from this study's results. The use of fractal dimensionality could be explored to supplement previous qualitative OC studies. FD as quantitative measure between of hierarchical alignment could be applied to studies that had previously demonstrated a qualitative link between hierarchical alignment and positive organizational outcomes. For example, recent qualitative studies that explored the nature of hierarchical alignment in human organizations, like those of Tronvoll et al. (2020) and Bertolotti et al. (2019) could be expanded to include quantitative fractal dimension measures. Similarly, FD could be applied to social research that identified barriers resulting from hierarchical levels. Meske et al. (2020) demonstrated that hierarchy can act as a barrier to communication across power levels, impeding organizational learning. Meske et al. (2020) intimated that hierarchies must be aligned to promote learning required as a prerequisite of change but had no quantitative way of assessing alignment. Researchers could build upon the Meske et al.'s (2020) work using fractal measures to investigate the link between changes in learning and learning outcomes.

Another research implication of this study is that it confirmed Tronvoll et al.'s (2020) observation that alignment across organizational boundaries was crucial to successful change. The fractal property of scale invariant self-replication helps explicate Q. Chen et al.'s (2021) assertion that dyadic alignment between organizations and individuals was fundamentally important for successful business practice. However, it is still unclear whether OC alignment causes change or if the OC alignment is coincidentally linked to OC success. Although it is tempting for me to assert that fractal alignment causes OC success, my study was insufficient to declare causality, and merely demonstrated a positive association between FD predictor and OC success criterion variables. In Chapter 1, I described the temporal link between the alignment of beliefs and actions during a change process and the realization of the change outcome. Because beliefs and actions precede OC outcomes, there is a predecessor-successor relationship between the FD predictor variable and the OC success criterion variable. Because OC actions precede attributions of success I infer from the correlation between FD and OCC success is that it is possible that hierarchical alignment is a causal factor in OC success. An implication for future research could be an expansion of this work to include quantitative studies exploring the degree to which OC alignment causes OC success.

My study represented a proof-of-concept indicating that there was a reasonable possibility that SOFT applies to human systems like organizations. My results reinforced the advice of Voss et al. (2017) for social researchers to explore beyond the metaphorical use of fractals and narrative descriptions of self-organization. My study also demonstrated that concepts that have historically been the purview of the physical sciences could be adapted to help social researchers quantify or measure complex organizational behavior. A research implication of my work is that is likely that other physical science notions could also be used to enhance the depth of social science investigations. For example, fractals could be used to quantitatively assess Zelt et al.'s (2018) observation that organizational activities and organizational processes in general were a collective of repeated patterns. Instead of observing the interdependencies between workers and other levels of the organization, FD could be used to quantify and compare the strength of the interdependencies or the inertial extent of the organization.

This work adds quantitative support to Vakili's (2018) notion that nonlinear and self-replicating responses within living systems can be characterized through fractal scale and dimensionality measures. Perhaps this research provides evidence for an incremental step toward that goal. An implication of this work is that could help open the door for additional fractal studies outside the field of organizational change. For example, Schirmer and Geithner (2018) evaluated how the four hierarchical levels within organizations utilized power in the leader-leader, leader-worker, worker-worker, and network-individual dyadic relationships described. Although the authors had not proposed a fractal approach to measuring change, they postulated that contradictions were caused by unlearning old patterns of behavior and indicated that different individuals and levels within the organization might not learn in a monolithic fashion. Although my survey instrument contained elements related to resistance to change, an adaptation of FD measures to Schirmer and Geithner's work could lead to quantitative assessments regarding how dyadic learning ripples through an organization by measuring fractal changes in dyadic relationships over time.

Virtually any study that presumes an alignment or self-replicating patterns across a social system could build upon the results from this study. S. Kim and Shin (2017) studied how a common vision of the goals through inspiration and empowerment was likely to provide a better roadmap for the desired behavior. The use of a SOFT to guide the development of a quantitative measure could aid in understanding and modeling the connection between empowerment and behavior at an organizational level. Groves (2020) suggested that the usefulness of a quantitative measure might shed light on understanding previously unquantified concepts like transformational leadership or the degree of change itself.

Human systems are complex, and many researchers suggest that we may never fully understand them. Katerelos and Tsekeris (2012) described human systems as chaotic but opined that the physical sciences could be the key to modeling their behavior. But using quantitative measures to enrich qualitative research is not the only implication of this work. Quantitative measures beget questions relating to why human systems follow measurable patterns. Ultimately, observed quantitative results improve qualitative inquiry by challenging researchers to understand what motivates predictable behavior. My study did not explain why self-replication was related to OC success. The implication for qualitative research is that my study's results could foster additional qualitative studies to understand what causes patterned alignment or to identify which behaviors are most important in achieving alignment.

Implications for Practice

McCoy (2022) wrote that U.S. aerospace firms struggle to contain costs in an ever-changing competitive industrial landscape. Aerospace firms adapt to the perceived economic, technical, and skills threat (McCoy, 2022) by constantly adapting through OC. However, as I described in Chapter 2, there are currently no practical measures for OC success that can be used *in situ* instead of retrospectively. Without a roadmap for OC success and a corresponding measure of progress toward the OC goal, it is not surprising that a majority of formal OC processes fail.

This work has several implications for practice. First, it reinforced the importance of hierarchical alignment in general. Perhaps aerospace management practices could be more successful at change by deliberately considering how a change will be managed across different levels of organizational hierarchy. Scholarly research has consistently demonstrated that an OC directive from leadership mandating a change in behavior is insufficient to guarantee its success (see Nye et al., 2010; Stame, 2010). A common vision is essential for effective change and must also be integrated across the organizational hierarchy before it can succeed (Sibbet, 2013). A change mandate is perceived and applied differently at the fractal belief and behavioral level, subject to capability, understanding, and interpretation of the need for change and the method by which to effect change (see Gibson & McDaniel, 2010). This research could eventually lead to a practical measure of hierarchical alignment based on FD that could be performed in real time. A real time measure of hierarchical alignment could assist organizational leaders in understanding which areas of the hierarchy are performing better than others or where the framing vision for change is not aligned.

In addition to a general awareness of alignment, this research could help leaders within organizations understand how to identify the fractal elements within their planned changes that need to be repeated across different hierarchical scales. Beer et al. (2016) stressed the importance of leadership using quantitative measures across all levels of the organization to facilitate successful business operations and change the working culture.

Nielsen and Lund (2018) characterized an organization by its ability to translate inputs into outcomes from the lowest level of the organization through the executive levels. I infer from my results that OC alignment can be measured, thereby providing leaders with a quantitative measure relating to OC success. If leaders within an organization knew which behaviors were fractal and how the fractals could be used to identify anomalous behaviors or beliefs in their organization, they could measure, and thereby have the visibility to manage OC success.

Another implication of this work for practice is that it could lead to fractal dimension measurement in other functions within the organization, not just for organizational change. Conceptually, using SOFT as a guide, any corporate process extending across administrative or functional domain boundaries might also show fractal behavior. The long-term implication of this work is that it could lead to improved real-time measures of dynamic processes within an organization. For example, creating and releasing an engineering drawing and subsequent procurement, building, and testing of the part resulting from the drawing requires significant coordination across an organization. Yin et al. (2022) described the coordination of product design as a substantial driver of cost and schedule in engineering organizations. Perhaps a measure of the fractal dimension related to how each process output moves in relation to its anticipated schedule could help identify problems with the design process.

Implications for Positive Social Change

Mazri (2021) described how a concurrent measure of change could dramatically facilitate a managers' ability to influence change outcomes. Ultimately, a real-time measure of change could reduce a portion of the trillions of dollars wasted by organizations failing to implement change strategies (see Business Wire, 2018). Reducing this wasted capital would result in improved operations and increased profitability for companies. More profitability through efficiency leads to higher job retention and improved workforce engagement (Musgrove et al., 2014).

Uka and Prendi (2021) described how workplace performance, worker engagement, and corresponding worker benefits were positively intertwined. Profitable organizations benefit society by providing more jobs and reinvestment of capital into the community (Hans & Vissa, 2021). With an improved concurrent measure of OC success, the money and effort wasted on failed change could be redirected to enrich the quality of the workers' jobs.

Improved worker job satisfaction is not the only advantage of a profitable company. With less waste, companies will invest more in socially responsible activities. Chenge (2020) noted that corporate profitability was strongly correlated with increased leader commitment to corporate social responsibility programs. Ojo et al. (2020) found that companies with higher profitability were more likely to increase their participation contribution to socially responsible activities like pollution control and social outreach programs. Carrasco and Vílchez (2022) confirmed that profitable companies were willing to invest in corporate social responsibility programs than non-profitable ones, especially as it related to investments in local economic development programs. By reducing the money wasted on failed change, more money is available to spend on positive social change efforts.

This work also contributed to positive social change by increasing the body of knowledge in social research so that improved methodologies can be utilized to understand and characterize social issues. In my literature review for organizational change, I found that approximately 4% of the search results from OC research were quantitative. Qualitative social research is essential for assessing certain kinds of social phenomena and addressing the “why” question pertaining to a social issue. However, quantitative research provides the ability to assess and quantify information regarding social issues. Eyisi (2016) wrote that the solution to social problems required that qualitative research be supported by quantitative facts to provide a holistic view of the issues. Because social research takes on significant and important issues, it also requires positivistic facts to sway leadership and decision-makers.

Research in social change does not cause social change, but it can enable policy makers to make informed decisions about the causes and the extent of a social issue (see Tawodzera et al. 2022). This study exemplifies how a qualitative analysis could facilitate new ways to view a topic like OC that had already been extensively studied. My literature review examined several sources who speculated that organizational hierarchies were fractal by nature. However, without a corresponding quantitative study, the speculations were unproven. Powell (2020) described the fundamental link between quantitative and qualitative methods in social change research. Powell described quantitative research as a critical support for positive social change because it provided a comprehensive platform by which social change agendas are funded and supported. An implication of this research is that other social change topics might benefit from the addition of a SOFT-based examination. For example, Wasserman and Clair (2011) described how a complex social topic like homelessness could benefit from viewing the problem as a scale-invariant fractal. Wasserman and Clair did not explicitly analyze the problem using fractal mathematics; however, their work would have been reinforced had it contained quantitative data as proof of their premise.

Conclusion

Croitoru et al. (2018) noted that there were very few contemporary organizational change studies that quantitatively associated change practice and performance outcomes. In this study, I explored the link between hierarchical alignment during an organizational change and organizational change success. I used a calculated fractal dimension as a measure of alignment based on the degree of agreement within thematic questions relating to dyadic hierarchical parings. The theoretical foundation for my study was Kurakin's self-organizing fractal theory. The results from my empirical study allowed me to conclude that there was a significant positive correlation between fractal dimension and organizational change success. I used two methods to calculate fractal dimension and both methods yielded similar correlative results. FD when calculated using the replication method was more closely correlated with OC success than FD measured by the pixel proximity method, however both correlations were statistically significant.

My study provided a proof-of-concept that there is evidence for self-scaling properties of behavior and beliefs across an organization undergoing change. I also showed that the fractal dimension is measurable and that the relative differences in magnitude between dimensional measures correlate with the OC outcome success. Using a fractal measure simplified the characterization of alignment because it did not require an understanding of the specific change initiative nor the motivations of the workforce undergoing the change.

Although my study successfully answered my research question, further work is needed to generalize these results beyond the scope of this study. I described several potential improvements to my survey, including that the fractal emergence survey instrument should be reduced in length and modified to add questions regarding specific dyadic relationships. Also, the study should be expanded outside the realm of North American aerospace workers. I opined that other social research studies could leverage this work to develop quantitative measures of change.

This study contributes to the scholarly research by providing evidence that measurable self-organizing fractal behaviors are present in OC systems. Follow-on research stemming from this study could help close the knowledge gap associated with the use of physics-based science and social science research methods. At a minimum, this research substantiated earlier studies that envisaged the use of fractal measures in social research. This study appears to be the first of its kind to quantitatively substantiate the link between fractal properties and OC success. As a proof-of-concept validation of SOFT, this work paves the way for similar fractal studies in additional or adjacent social research scenarios.

It appears that the adage “If you can’t measure it, you can’t manage it” applies to organizational change practice. Even after decades of OC research, a majority of organizational changes fail to achieve their desired outcomes. This study contributed to management practice by providing the basis for the development of a real-time measurement of alignment of beliefs and behaviors across the organizational hierarchy. A real time hierarchical alignment measurement would facilitate the management of the organizational change process.

This study contributed to positive social change by providing a mechanism that may lead to a reduction in the economic burden of wasted time and money spent on failed change processes. Lower failure rates would result in lower operational costs and might enable a more profitable organization. Profitable organizations would, in turn, facilitate improved workplace conditions and increased employee engagement. Improved profitability could also promote improved local economies through both increased employment rates and local improvements. Perhaps the biggest contribution my research could have for positive social change is through the application of SOFT to support qualitative research in socially relevant issues with measures of underlying self-replicating patterns which could aid in gaining support for change.

References

Abbott, P., Zheng, Y., Du, R., & Willcocks, L. (2013). From boundary spanning to creolization: A study of Chinese software and services outsourcing vendors. *The Journal of Strategic Information Systems*, *22*(2), 121–136. https://doi.org/10.1016/j.jsis.2013.02.002

Abdallah, S., Malik, M., & Chaudhry, U. (2020). An actor–network theory perspective for "lean" interventions in manufacturing firms. *TQM Journal*, *32*(6), 1487–1506. https://doi.org/10.1108/TQM-05-2019-0146

Abu-Alhaija, A. S. (2019). From epistemology to structural equation modeling: An essential guide in understanding the principles of research philosophy in selecting the appropriate methodology. *Australian Journal of Basic and Applied Sciences*, *13*(9), 122–128. https://doi.org/10.22587/ajbas.2019.13.9.12

Ai, S., Du, R., Straub, D. W., Maruping, L. M., & Miao, Y. (2019). Measuring creolization in IT outsourcing: Instrument development and validation. *International Journal of Information Management*, *47*, 16–30. https://doi.org/10.1016/j.ijinfomgt.2018.12.012

Aksom, H. (2022). Institutional inertia and practice variation. *Journal of Organizational Change Management*, *35*(3), 463–487. https://doi.org/10.1108/JOCM-07-2021-0205

Allison, P. D. (1999). What are the assumptions of multiple regression? In *Multiple regression: A primer* (pp. 119–136). Pine Forge Press.

American Institute of Aeronautics and Astronautics. (n.d.-a). *About AIAA*.

https://www.aiaa.org/about

American Institute of Aeronautics and Astronautics. (n.d.-b). *Diversity and inclusion*. https://www.aiaa.org/get-involved/committees-groups/Diversity-and-Inclusion

Amiripour, P., Dossey, J. A., & Shahvarani, A. (2017). Impact of organizational inertia and dynamic capabilities on educational performance of the charitable societies and its impact on mathematical performance of elementary at-risk students. *Journal of New Approaches in Educational Research*, *6*(1), 37–49. https://doi.org/10.7821/naer.2017.1.199

Andreeva, T. E. (2008). Can organizational change be planned and controlled? Evidence from Russian companies. *Human Resource Development International*, *11*(2), 119–134. https://doi.org/10.1080/13678860801932923

Andrianova, E. G., Golovin, S. A., Zykov, S. V., Lesko, S. A., & Chukalina, E. R. (2020). Review of modern models and methods of analysis of time series of dynamics of processes in social, economic and socio-technical systems. *Russian Technological Journal*, *8*(4), 7–45. https://doi.org/10.32362/2500-316X-2020-8-4-7-45

Appelbaum, N. P., Santen, S. A., Vota, S., Wingfield, L., Sabo, R., & Yaghmour, N. (2019). Threats to reliability and validity with resident wellness surveying efforts. *Journal of Graduate Medical Education*, *11*(5), 543–549. https://doi.org/10.4300/JGME-D-19-00216.1

Araujo, P., & Frøyland, L. (2007). Statistical power and analytical quantification. *Journal of Chromatography B*, *847*(2), 305-308.

https://doi.org/10.1016/j.jchromb.2006.10.002

Axelrod, R. H., & Axelrod, E. M. (2017). The scholar-practitioner mindset: How texts and experience influence organizational change practice. *Academy of Management Review*, *42*(3), 561–571. https://doi.org/10.5465/amr.2016.0224

Azam, M. T., Bush, H. M., Coker, A. L., & Westgate, P. M. (2021). Effect sizes and intra-cluster correlation coefficients measured from the Green Dot High School study for guiding sample size calculations when designing future violence prevention cluster randomized trials in school settings. *Contemporary Clinical Trials Communications*, *23*, Article 100831. https://doi.org/10.1016/j.conctc.2021.100831

Bagnaresi, D., Barbini, F. M., & Battilani, P. (2018). At the intersection of business history and organization theory: An interdisciplinary and process-based method for studying organizational change. In *European Conference on Research Methodology for Business and Management Studies* (pp. 36–43). Academic Conferences International Limited. https://www.proquest.com/conference-papers-proceedings/at-intersection-business-history-organization/docview/2088045811/se-2?accountid=14872

Barkley, D., Hatsis, P., Glick, J., Li, W., & Flarakos, J. (2020). Dixon's Q-test and student's t-test to assess analog internal standard response in nonregulated LC–MS/MS bioanalysis. *Bioanalysis*, *12*(21), 1535–1543. https://doi.org/10.4155/bio-2020-0207

Barlin, J. N., Zhou, Q., St. Clair, C. M., Iasonos, A., Soslow, R. A., Alektiar, K. M., Hensley, M. L., Leitao, M. M., Jr., Barakat, R. R., & Abu-Rustum, N. R. (2013). Classification and regression tree (CART) analysis of endometrial carcinoma: Seeing the forest for the trees. *Gynecologic Oncology*, *130*(3), 452–456. https://doi.org/10.1016/j.ygyno.2013.06.009

Beer, M., Finnström, M., & Schrader, D. (2016). Why leadership training fails—and what to do about it. *Harvard Business Review*, *94*(10), 50–57. https://hbr.org/2016/10/why-leadership-training-fails-and-what-to-do-about-it

Ben-Menahem, S. M., Kwee, Z., Volberda, H. W., & Van Den Bosch, F. A. J. (2013). Strategic renewal over time: The enabling role of potential absorptive capacity in aligning internal and external rates of change. *Long Range Planning*, *46*(3), 216–235. https://doi.org/10.1016/j.lrp.2012.09.012

Bentley, F., O'Neill, K., Quehl, K., & Lottridge, D. (2020). Exploring the quality, efficiency, and representative nature of responses across multiple survey panels. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–12). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376671

Berberoglugil, B. M., & Şatir, S. (2012). Fractal organization management: University as a model. In *2012 15th International Conference on Interactive Collaborative Learning (ICL)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICL.2012.6402039

Bertolotti, F., Macrì, D. M., & Vignoli, M. (2019). Strategic alignment matrix: Supporting management coordination in complex organizations. *Journal of Accounting & Organizational Change*, *15*(4), 557–579.

https://doi.org/10.1108/JAOC-12-2017-0122

Biehl, A., Ermagun, A., & Stathopoulos, A. (2018). Modelling determinants of walking and cycling adoption: A stage-of-change perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 452–470. https://doi.org/10.1016/j.trf.2018.06.016

Bilan, Y., Hussain, H. I., Haseeb, M., & Kot, S. (2020). Sustainability and economic performance: Role of organizational learning and innovation. *Engineering Economics*, *31*(1), 93–103. https://doi.org/10.5755/j01.ee.31.1.24045

Black, J., & La Venture, K. (2018). The human factor to profitability: Leveraging people-centered cultures as meaningful organizations. *Public Integrity*, *20*(5), 444–458. https://doi.org/10.1080/10999922.2017.1364949

Blalock, H. M., Jr. (2018). *Causal inferences in nonexperimental research*. UNC Press.

Bollen, K. A., & Diamantopoulos, A. (2017). In defense of causal-formative indicators: A minority report. *Psychological Methods*, *22*(3), 581–596. https://doi.org/10.1037/met0000056

Bolman, L. G., & Deal, T. E. (2017). *Reframing organizations: Artistry, choice, and leadership* (6th ed.). Jossey-Bass.

Borgogni, L., Russo, S. D., & Latham, G. P. (2011). The relationship of employee perceptions of the immediate supervisor and top management with collective efficacy. *Journal of Leadership & Organizational Studies*, *18*(1), 5–13. https://doi.org/10.1177/1548051810379799

Botev, J. (2020). Self-integration in mediated-reality systems: A socio-technical perspective. In *2020 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)* (pp. 60–61). IEEE. https://doi.org/10.1109/ACSOS-C51401.2020.00030

Brandtner, E., & Freiling, J. (2021). Is dominant logic a value or a liability? On the explorative turn in the German power utility industry. *Journal of Entrepreneurship, Management and Innovation*, *17*(2), 125–157. https://doi.org/10.7341/20211725

Brantley, W. A. (2009). *The effect of mental models on creating organizational alignment around a change vision* [Doctoral dissertation, Walden University]. ScholarWorks.

Brick, J. M., & Kalton, G. (1996). Handling missing data in survey research. *Statistical Methods in Medical Research*, *5*(3), 215–238. https://doi.org/10.1177/096228029600500302

Brown, D. R., Rose, D., & Gordon, R. (2016). De-commoditizing change management: A call for the re-positioning of change management on IT projects. *Journal of Organizational Change Management*, *29*(5), 793–803. https://doi.org/10.1108/JOCM-07-2015-0116

Burkholder, G. J., & Burbank, P. M. (2019). Philosophical foundations and the role of theory in research. In G. J. Burkholder, K. A. Cox, L. M. Crawford, & J. Hitchcock (Eds.), *Research design and methods: An applied guide for the scholar-practitioner* (pp. 13–34). SAGE Publications. https://us.sagepub.com/en-us/nam/research-design-and-methods/book262895

Burkholder, G. J., Cox, K. A., & Crawford, L. M. (2016). *The scholar-practitioner's guide to research design.* Laureate Publishing. https://scholarworks.waldenu.edu/facpubs/277

Business Wire. (2018, February 15). *$1 million wasted every 20 seconds by organizations around the world*. Business Wire. https://www.businesswire.com/news/home/20180215005610/en/1-Million-Wasted-20-Seconds-Organizations-World

Canadian Council for Aviation & Aerospace. (2018). *Labour market information report*. https://www.avaerocouncil.ca/sites/default/files/files/ccaa_lmi_report_march_2018_-_final.pdf

Cao, T., Locatelli, G., Smith, N., & Zhang, L. (2021). A shared leadership framework based on boundary spanners in megaprojects. *International Journal of Managing Projects in Business*, *14*(5), 1065–1092. https://doi.org/10.1108/IJMPB-03-2020-0090

Carrasco, P. O., & Vílchez, V. F. (2022). Sending corporate social responsibility signals: What organizational characteristics must be met?. *Revista Brasileira de Gestão de Negócios*, *24*, 92-111. https://doi.org/10.7819/rbgn.v24i1.4146

Caulfield, J. L., Lee, F. K., & Richards, B. A. (2021). Leadership as an art: An enduring concept framed within contemporary leadership. *Leadership & Organization Development Journal*, *42*(5), 735–747. https://doi.org/10.1108/LODJ-11-2020-0524

Chen, Q., Hall, D. M., Adey, B. T., & Haas, C. T. (2021). Identifying enablers for coordination across construction supply chain processes: A systematic literature review. *Engineering, Construction and Architectural Management*, *28*(4), 1083–1113. https://doi.org/10.1108/ECAM-05-2020-0299

Chen, Y., & Long, Y. (2021). Spatial signal analysis based on wave-spectral fractal scaling: A case of urban street networks. *Applied Sciences*, *11*(1), Article 87. https://doi.org/10.3390/app11010087

Chenge, M. (2020). How does firm's performance affect corporate social responsibility disclosure: The panel regression analysis on China listed firms. *2020 16th Dahe Fortune China Forum and Chinese High-Educational Management Annual Academic Conference (DFHMC), High-Educational Management Annual Academic Conference (DFHMC), 2020 16th Dahe Fortune China Forum and Chinese, DFHMC*, 130–137. https://doi.org/10.1109/DFHMC52214.2020.00034

Chudoba, B. (n.d.). *How much time are respondents willing to spend on your survey?* SurveyMonkey. Retrieved March 26, 2022, from https://www.surveymonkey.com/curiosity/survey_completion_times/

Cockcroft, T. (2019). Institutional hybridity and cultural isomorphism in contemporary policing. *International Journal of Police Science & Management*, *21*(4), 218–229. https://doi.org/10.1177/1461355719889462

Corritore, M., Goldberg, A., & Srivastava, S. B. (2020). The new analytics of culture: What email, Slack, and Glassdoor reveal about your organization. *Harvard Business Review*, *98*(1), 76–83. https://hbr.org/2020/01/the-new-analytics-of-culture

Couper, M. P., Singer, E., Conrad, F. G., & Groves, R. M. (2008). Risk of disclosure, perceptions of risk, and concerns about privacy and confidentiality as factors in survey participation. *Journal of Official Statistics*, *24*(2), 255–275. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3096944/

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Croitoru, G., Robescu, V. O., Oprisan, O., Duica, M., & Manolache, D. C. (2018). T. *Journal of Science and Arts*, *18*(1), 139–158. http://www.josa.ro/docs/josa_2018_1/a_10_Croitoru_139-158.pdf

Crossman, A. (2020, February 2). *An overview of qualitative research methods*. ThoughtCo. https://www.thoughtco.com/qualitative-research-methods-3026555

Curtis, E. A., Comiskey, C., & Dempsey, O. (2016). Importance and use of correlational research. *Nurse Researcher*, *23*(6), 20–25. https://doi.org/10.7748/nr.2016.e1382

Daru, A. F., Hanif, M. B., & Widodo, E. (2021). Improving neural network performance with feature selection using Pearson correlation method for diabetes disease detection. *Jurnal Informatika*, *9*(1), 123–130. https://doi.org/10.30595/juita.v9i1.9941

Das, S. K., Cenanovic, M., & Zhang, J. (2019). A physics-based estimation of mean curvature normal vector for triangulated surfaces. *arXiv preprint arXiv:1902.02271*. https://doi.org/10.15673/tmgc.v12i1.1377

Del Águila, M. R., & González-Ramírez, A. R. (2014). Sample size calculation. *Allergologia et immunopathologia*, *42*(5), 485–492.

https://doi.org/10.1016/j.aller.2013.03.008

Deloitte. (2016). *The next era of aerospace and defense: How to outperform in an environment of innovative disruption* [Report]. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/manufacturing/us-manu-next-era-of-aerospace-and-defense.pdf

Deni, A., Priansa, D. J., Darmo, I. S., Saribanon, E., Riswanto, A., Sumaryadi, S., & Ramdan, A. M. (2020). Organizational competency and innovation capability: The influence of knowledge management on business performance. *Quality - Access to Success*, *21*(179), 47–51. https://www.proquest.com/scholarly-journals/organizational-competency-innovation-capability/docview/2463699791/se-2?accountid=14872

Dissanayake, I., Jeyaraj, A., & Nerur, S. P. (2021). The impact of structure and flux of corporate boards on organizational performance: A perspective from the information technology industry. *Journal of Strategic Information Systems*, *30*(2), Article 101667. https://doi.org/10.1016/j.jsis.2021.101667

Dorling, J. L. (2017). Impact of psychological capital on the resistance to change during post-merger integration: A theoretical model. *Journal of Organizational Change Management*, *30*(6), 936–956. https://doi.org/10.1108/JOCM-11-2015-0199

Downing, S. M. (2004). Reliability: On the reproducibility of assessment data. *Medical Education*, *38*(9), 1006–1012. https://doi.org/10.1111/j.1365-2929.2004.01932.x

Duesbery, L., & Twyman, T. (2020). *100 Questions (and answers) about action research*. SAGE Publications. https://doi.org/10.4135/9781544305455

Duman, A., & Inel, Y. (2019). Review of master's theses in the field of social studies education between 2008 and 2014. *Universal Journal of Educational Research*, *7*(1), 66–73. https://doi.org/10.13189/ujer.2019.070109

Eason, K. (2014). Afterword: The past, present and future of sociotechnical systems theory. *Applied Ergonomics*, *45*(2 Part A), 213–220. https://doi.org/10.1016/j.apergo.2013.09.017

Edmonds, W. A., & Kennedy, T. D. (2017). *An applied guide to research designs: Quantitative, qualitative, and mixed methods* (2nd ed.). SAGE Publications. https://doi.org/10.4135/9781071802779

Edwards, P. N. (2003). Infrastructure and modernity: Force, time, and social organization in the history of sociotechnical systems. In T. J. Misa, P. Brey, & A. Feenberg (Eds.), *Modernity and technology* (pp. 185–226). MIT Press. https://www.proquest.com/docview/2463699791/fulltextPDF/3CB6024DF6794E70PQ/1?accountid=14872

Eroshenko, T., Fedoseenkov, A., Sorokin, G., & Malyshev, A. (2019). Methodology of creative work: Transformation structure. *SHS Web of Conferences*, *72*, Article 01002. https://doi.org/10.1051/shsconf/20197201002

Esch, J. (2004). A macroscopic view of self-replication. *Proceedings of the IEEE*, *92*(12), 1927–1928. https://doi.org/10.1109/JPROC.2004.837628

Evermann, J. (2012). *Covariance based structural equation modelling* [Presentation slides]. Memorial University of Newfoundland. https://users.ugent.be/~yrosseel/lavaan/evermann_slides.pdf

Eyisi, D. (2016). The usefulness of qualitative and quantitative approaches and methods in researching problem-solving ability in science education curriculum. *Journal of Education and Practice*, 7(15), 91–100. https://files.eric.ed.gov/fulltext/EJ1103224.pdf

Fang, Y., Dai, X., & Zhang, X. (2021). An empirical study of the relationship between inclusive leadership and business model innovation. *Leadership & Organization Development Journal*, *42*(3), 480–494. https://doi.org/10.1108/LODJ-11-2019-0484

Farooq, U., Ahmed, M., Hussain, S., Hussain, F., Naseem, A., & Aslam, K. (2021). Blockchain-based software process improvement (BBSPI): An approach for SMEs to perform process improvement. *IEEE Access*, *9*, 10426–10442. https://doi.org/10.1109/ACCESS.2021.3049904

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Feeko, P., & Fuller, S. (2021). *2021 aerospace and defense (A&D) workforce study* [White paper]. Ernst & Young. https://www.aiaa.org/docs/default-source/default-document-library/whitepapers/2021workforcestudywhitepaper.pdf

Fink, A. (2015). *How to conduct surveys: A step-by-step guide* (6th ed.). SAGE Publications.

Fischer, E. M. (2016). *The next era of aerospace and defense: How to outperform in an environment of innovative disruption* [White paper]. Deloitte Consulting, LLP.

https://www2.deloitte.com/content/dam/Deloitte/us/Documents/manufacturing/us-manu-next-era-of-aerospace-and-defense.pdf.

Fisher, C. B., & Anushko, A. E. (2008). Research ethics in social science. In P. Alasuutari, L. Bickman, & J. Brannen (Eds.), *The SAGE handbook of social research methods* (pp. 95–109). SAGE Publications. https://dx.doi.org/10.4135/9781446212165

Fryer, P., & Ruis, J. (2004, June 18). *What are fractal systems?: A brief description of 'complex adaptive and emergent systems' (CAES)*. Fractal.org. http://www.fractal.org/Fractal-Systems.htm

Fugard, A. J. B., & Potts, H. W. W. (2015). Supporting thinking on sample sizes for thematic analyses: A quantitative tool. *International Journal of Social Research Methodology*, *18*(6), 669–684. https://doi.org/10.1080/13645579.2015.1005453

Gaither, S. E. (2018). The multiplicity of belonging: Pushing identity research beyond binary thinking. *Self and Identity*, *17*(4), 443–454. https://doi.org/10.1080/15298868.2017.1412343

Gaughan, M., & Bozeman, B. (2016). Using the prisms of gender and rank to interpret research collaboration power dynamics. *Social Studies of Science*, *46*(4), 536–558. https://doi.org/10.1177/0306312716652249

Gey, S., & Nedelec, E. (2005). Model selection for CART regression trees. *IEEE Transactions on Information Theory*, *51*(2), 658–670. https://doi.org/10.1109/TIT.2004.840903

Gibson, C. B., & McDaniel, D. M. (2010). Moving beyond conventional wisdom:

Advancements in cross-cultural theories of leadership, conflict, and teams. *Perspectives on Psychological Science*, *5*(4), 450–462. https://doi.org/10.1177/1745691610375560

Giorgio, L., Mascia, D., & Pallotti, F. (2020). Organizational redesign, knowledge transfer, and the formation of new boundary-spanning ties. *Academy of Management Proceedings*, (1), 14639. https://doi.org/10.5465/AMBPP.2020.14639abstract

Gocheva-Ilieva, S., Kulina, H., & Ivanov, A. (2021). Assessment of students' achievements and competencies in mathematics using CART and CART ensembles and bagging with combined model improvement by MARS. *Mathematics*, *9*(1), Article 62. https://doi.org/10.3390/math9010062

Goekoop, R., & de Kleijn, R. (2021). Permutation entropy as a universal disorder criterion: How disorders at different scale levels are manifestations of the same underlying

Groves, K. S. (2020). Testing a moderated mediation model of transformational leadership, values, and organization change. *Journal of Leadership & Organizational Studies*, *27*(1), 35–48. https://doi.org/10.1177/1548051816662614

Hagsall, A. E., Ahituv, N., & Naveh, N. (2019). Effective assimilation of technological innovation in an organization characterized as a complex adaptive system. *Journal of Innovation Management*, *7*(2), 38–58. https://doi.org/10.24840/2183-0606_007.002_0004

Haken, H., & Portugali, J. (2021). Information and self-organization II: Steady state and phase transition. *Entropy*, *23*(6), Article 707. https://doi.org/10.3390/e23060707

Halcomb, E. J. (2019). Mixed methods research: The issues beyond combining methods. *Journal of Advanced Nursing*, *75*(3), 499–501. https://doi.org/10.1111/jan.13877

Halcomb, E., & Hickman, L. (2015). Mixed methods research. *Nursing Standard*, *29*(32), 41–47. https://doi.org/10.7748/ns.29.32.41.e8858

Hallencreutz, J., & Turner, D. (2011). Exploring organizational change best practice: Are there any clear-cut models and definitions? *International Journal of Quality and Service Sciences*, *3*(1), 60–68. https://doi.org/10.1108/17566691111115081

Han, X., Zhan, C., & Li, G. (2021). Fractal-dimension-based walking trajectory analysis: A case study in museum J. Armand Bombardier. *Advances in Civil Engineering*, 1–7. https://doi.org/10.1155/2021/9038686

Hans, L. K., & Vissa, B. (2021). *Who gives back? Evidence from India on successful entrepreneurial exit and involvement in philanthropy* [Report]. INSEAD. https://doi.org/10.1287/orsc.2022.1572

Harms, P. D., & Credé, M. (2010). Emotional intelligence and transformational and transactional leadership: A meta-analysis. *Journal of Leadership & Organizational Studies*, *17*(1), 5–17. https://doi.org/10.1177/1548051809350894

Hassan, M. K., Hassan, M. Z., & Islam, N. (2013). Emergence of fractals in aggregation with stochastic self-replication. *Physical Review E*, *88*(4), Article 042137. https://doi.org/10.1103/PhysRevE.88.042137

Heileman, G. L., Hickman, M., Slim, A., & Abdallah, C. T. (2017, June). *Characterizing the complexity of curricular patterns in engineering programs* [Paper presentation]. 2017 ASEE Annual Conference & Exposition, Columbus, OH, United States. https://doi.org/10.18260/1-2--28029

Helmich, E., Boerebach, B. C. M., Arah, O. A., & Lingard, L. (2015). Beyond limitations: Improving how we handle uncertainty in health professions education research. *Medical Teacher*, *37*(11), 1043–1050. https://doi.org/10.3109/0142159X.2015.1073239

Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2019). Literature review: Machine learning techniques applied to financial market prediction. *Expert Systems with Applications*, *124*, 226–251. https://doi.org/10.1016/j.eswa.2019.01.012

Heorhiadi, N., Druhov, O., Vilhutska, R., Bets, M., Stoianovskyi, A., & Folwarski, M. (2018). Organizational development in banks management systems. *Banks and Bank Systems*, *13*(3), 1–11. https://doi.org/10.21511/bbs.13(3).2018.01

Hill, B. D. (2011). *The sequential Kaiser-Meyer-Olkin procedure as an alternative for determining the number of factors in common-factor analysis: A Monte Carlo simulation* (Publication No. 3474663) [Doctoral dissertation, Oklahoma State University]. ProQuest Dissertations Publishing. https://www.proquest.com/dissertations-theses/sequential-kaiser-meyer-olkin-procedure-as/docview/898980750/se-2?accountid=14872

Hoff, T., & Scott, S. (2017). The strategic nature of individual change behavior: How physicians and their staff implement medical home care. *Health Care Management Review*, *42*(3), 226–236. https://doi.org/10.1097/HMR.0000000000000109

Hopkins, W. E., Mallette, P., & Hopkins, S. A. (2013). Proposed factors influencing strategic inertia/strategic renewal in organizations. *Academy of Strategic Management Journal*, *12*(2), 77. https://www.proquest.com/docview/1465244670?pq-origsite=gscholar&fromopenview=true

Hower, K. I., Pfaff, H., Kowalski, C., Wensing, M., & Ansmann, L. (2019). Measuring change attitudes in health care organizations: Psychometric evaluation of the "Change Attitude Scale". *Journal of Health Organization and Management*, *33*(3), 266–285. https://doi.org/10.1108/JHOM-06-2018-0177

Hussain, S. T., Lei, S., Akram, T., Haider, M. J., Hussain, S. H., & Ali, M. (2018). Kurt Lewin's change model: A critical review of the role of leadership and employee involvement in organizational change. *Journal of Innovation & Knowledge*, *3*(3), 123–127. https://doi.org/10.1016/j.jik.2016.07.002

IBM. (2021a, November 9). *SPSS Statistics 28.0.0: Collinearity diagnostics.* *https://www.ibm.com/docs/en/spss-statistics/28.0.0?topic=sales-collinearity-diagnostics*

IBM. (2021b, November 9). *SPSS Statistics 28.0.0: KMO and Bartlett's Test.* *https://www.ibm.com/docs/en/spss-statistics/28.0.0?topic=detection-kmo-bartletts-test*

Ichikawa, M., & Konishi, S. (2008). Constructing second-order accurate confidence intervals for communalities in factor analysis. *British Journal of Mathematical and Statistical Psychology*, *61*(2), 361–378.

https://doi.org/10.1348/000711007X204198

Israel, G. D. (2009). *Determining sample size* (Fact Sheet No. PEOD6). University of Florida. https://www.psycholosphere.com/Determining%20sample%20size%20by%20Glen%20Israel.pdf

Jabri, M. (2017). *Managing organizational change: Process, social construction and dialogue* (2nd ed.). Bloomsbury.

Jacob, K., Paulick-Thiel, C., Teebken, J., Veit, S., & Singer-Brodowski, M. (2021). Change from within: Exploring transformative literacy in public administrations to foster sustainability transitions. *Sustainability*, *13*(9), Article 4698. https://doi.org/10.3390/su13094698

Jakobsen, J. C., Gluud, C., Wetterslev, J., & Winkel, P. (2017). When and how should multiple imputation be used for handling missing data in randomised clinical trials – A practical guide with flowcharts. *BMC Medical Research Methodology*, *17*(1), Article 162. https://doi.org/10.1186/s12874-017-0442-1

Janmaimool, P. (2017). The role of descriptive social norms, organisational norms and personal norms in explaining solid waste management behaviours in workplaces. *Journal of Organizational Change Management*, *30*(2), 184–198. https://doi.org/10.1108/JOCM-12-2016-0265

Jayatilleke, S., & Lai, R. (2018). A systematic review of requirements change management. *Information and Software Technology*, *93*, 163–185. https://doi.org/10.1016/j.infsof.2017.09.004

Jevtić, M., Jovanović, M., & Krivokapić, J. (2018). A new approach to measuring the correlation of organizational alignment and performance. *Management: Journal of Sustainable Business and Management Solutions in Emerging Economies*, *23*(1), 41–52. https://doi.org/10.7595/management.fon.2017.0029

Jobst, L. J., Bader, M., & Moshagen, M. (2021). A tutorial on assessing statistical power and determining sample size for structural equation models. *Psychological Methods*. https://doi.org/10.1037/met0000423

Johansson, U., Sönströd, C., Löfström, T., & Boström, H. (2022). Rule extraction with guarantees from regression models. *Pattern Recognition*, *126*, Article 108554. https://doi.org/10.1016/j.patcog.2022.108554

Jones-Schenk, J. (2019). 70% failure rate: An imperative for better change management. *The Journal of Continuing Education in Nursing*, *50*(4), 148–149. https://doi.org/10.3928/00220124-20190319-03

Joseph, N. (2019). The fractal organization: Creating enterprises of tomorrow. *South Asian Journal of Management, 26*(1), 183–186. https://www.proquest.com/docview/2251595210?pq-origsite=gscholar&fromopenview=true

Karim, M., Furnaz, S., Buksh, A. R., Beg, M. A., Khan, M. S., & Moiz, B. (2019). Sample size calculation in medical research. In *2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)* (pp. 1–5). IEEE. https://doi.org/10.1109/MACS48846.2019.9024807

Katerelos, I., & Tsekeris, C. (2012). Reconsidering social dynamics: Fundamentality and social simulations. *TripleC*, *10*(1), 122–125. https://doi.org/10.31269/triplec.v10i1.406

Kattner, N., Mehlstaeubl, J., Becerril, L., & Lindemann, U. (2018). Data analysis in engineering change management – Improving collaboration by assessing organizational dependencies based on past engineering change information. In *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 617–621). IEEE. https://doi.org/10.1109/IEEM.2018.8607469

Keiding, N., & Louis, T. A. (2018). Web-based enrollment and other types of self-selection in surveys and studies: Consequences for generalizability. *Annual Review of Statistics & Its Application*, *5*, 25–47. https://doi.org/10.1146/annurev-statistics-031017-100127

Kenton, W. (2021, August 4). *Durbin Watson statistic definition*. Investopedia. https://www.investopedia.com/terms/d/durbin-watson-statistic.asp

Kim, H.-W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quarterly*, *33*(3), 567–582. https://doi.org/10.2307/20650309

Kim, S., & Shin, M. (2017). The effectiveness of transformational leadership on empowerment: The roles of gender and gender dyads. *Cross Cultural & Strategic Management*, *24*(2), 271–287. https://doi.org/10.1108/CCSM-03-2016-0075

King, D., & Land, C. (2018). The democratic rejection of democracy: Performative failure and the limits of critical performativity in an organizational change project.

Human Relations, *71*(11), 1535–1557. https://doi.org/10.1177/0018726717751841

King, M. L. (1981). The alternative Durbin-Watson test: An assessment of Durbin and Watson's choice of test statistic. *Journal of Econometrics*, *17*(1), 51–66. https://doi.org/10.1016/0304-4076(81)90058-0

King, S., Hopkins, M., & Cornish, N. (2018). Can models of organizational change help to understand 'success' and 'failure' in community sentences? Applying Kotter's model of organizational change to an integrated offender management case study. *Criminology & Criminal Justice*, *18*(3), 273–290. https://doi.org/10.1177/1748895817721274

Kluge, A., Schüffler, A. S., Thim, C., Haase, J., & Gronau, N. (2019). Investigating unlearning and forgetting in organizations. *The Learning Organization*, *26*(5), 518–533. https://doi.org/10.1108/TLO-09-2018-0146

Koehler, J. J. (2020). Forensic source conclusions: Twenty threats to validity. *Zeitschrift Fur Psychologie*, *228*(3), 149–161. https://doi.org/10.1027/2151-2604/a000413

König, A., Graf-Vlachy, L., & Schöberl, M. (2021). Opportunity/Threat Perception and Inertia in Response to Discontinuous Change: Replicating and Extending Gilbert (2005). *Journal of Management*, *47*(3), 771–816. https://doi.org/10.1177/0149206320908630

Kost, R. G., & da Rosa, J. C. (2018). Impact of survey length and compensation on validity, reliability, and sample characteristics for ultrashort-, short-, and long-research participant perception surveys. *Journal of Clinical and Translational*

Science, *2*(1), 31–37. https://doi.org/10.1017/cts.2018.18

Kovač, V. B., & Cameron, D. L. (2021). Are we talking about the same thing? A survey of preschool workers' attitudes and beliefs about bullying. *Child Care in Practice*. Advance online publication. https://doi.org/10.1080/13575279.2021.1951167

KPMG. (2014). *Business transformation and the corporate agenda* [Report]. https://advisory.kpmg.us/articles/2017/business-transformation-and-the-corporate-agenda.html

Kurakin, A. (2011). The self-organizing fractal theory as a universal discovery method: The phenomenon of life. *Theoretical Biology and Medical Modelling*, *8*(1), Article 4. https://doi.org/10.1186/1742-4682-8-4

Laerd Statistics. (n.d.). *ANOVA with repeated measures using SPSS statistics*. Retrieved September 11, 2021, from https://statistics.laerd.com/spss-tutorials/one-way-anova-repeated-measures-using-spss-statistics-2.php

Lang, K. M., & Little, T. D. (2018). Principled missing data treatments. *Prevention Science*, *19*(3), 284–294. https://doi.org/10.1007/s11121-016-0644-5

Lawrence, S., & Botes, V. (2011). Accounting and organizational change: An autopoietic view. *Journal of Global Business & Technology*, *7*(1), 74–85. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=bth&AN=67065835&site=eds-live&scope=site

Lazzarini, S. G. (2020). The nature of the social firm: Alternative organizational forms for social value creation and appropriation. *Academy of Management Review*, *45*(3), 620-645. https://doi.org/10.5465/amr.2018.0015

Leedy, P. D., & Ormrod, J. E. (2005). *Practical research* (9th ed.). Merrill

Lehdonvirta, V., Oksanen, A., Räsänen, P., & Blank, G. (2021). Social media, web, and panel surveys: Using non-probability samples in social and policy research. *Policy & Internet*, *13*(1), 134–155. https://doi.org/10.1002/poi3.238

Lewis, K. (2003). Measuring transactive memory systems in the field: Scale development and validation. *Journal of Applied Psychology*, *88*(4), 587–604. https://doi.org/10.1037/0021-9010.88.4.587

Leydens, J. A., Johnson, K., Claussen, S., Blacklock, J., Moskal, B. M., & Cordova, O. (2018, June 23–27). *Measuring change over time in sociotechnical thinking: A survey/validation model for sociotechnical habits of mind* [Paper presentation]. 2018 ASEE Annual Conference & Exposition, Salt Lake City, UT, United States. 10.18260/1-2--30794

Li, J., Liu, M., & Liu, X. (2016). Why do employees resist knowledge management systems? An empirical study from the status quo bias and inertia perspectives. *Computers in Human Behavior*, *65*, 189–200. https://doi.org/10.1016/j.chb.2016.08.028

Lind, M. R., & Sulek, J. M. (1994). A Newtonian metaphor for organizational change. *IEEE Transactions on Engineering Management*, *41*(4), 375–383. https://doi.org/10.1109/17.364561

Lindberg, E. (2014). Principals with and without performance measures means no change? *Journal of Organizational Change Management*, *27*(3), 520–531. https://doi.org/10.1108/JOCM-07-2013-0113

Lindsay, B., Smit, E., & Waugh, N. (2018, February 5). *How the implementation of organizational change is evolving*. McKinsey & Company. https://www.mckinsey.com/business-functions/mckinsey-implementation/our-insights/how-the-implementation-of-organizational-change-is-evolving

Liu, H., Liu, T., Jiang, J., Cheng, J., Liu, Y., Li, D., Dong, C., Niu, H., Li, S., Zhang, J., Brodaty, H., Sachdev, P., & Wen, W. (2020). Differential longitudinal changes in structural complexity and volumetric measures in community-dwelling older individuals. *Neurobiology of Aging*, *91*, 26–35. https://doi.org/10.1016/j.neurobiolaging.2020.02.023

Liu, J., Gatzweiler, F. W., & Kumar, M. (2021). An evolutionary complex systems perspective on urban health. *Socio-Economic Planning Sciences*, *75*, Article 100815. https://doi.org/10.1016/j.seps.2020.100815

Loch, K. D., Straub, D. W., & Kamel, S. (2003). Diffusing the Internet in the Arab world: The role of social norms and technological culturation. *IEEE Transactions on Engineering Management*, *50*(1), 45–63. https://doi.org/10.1109/TEM.2002.808257

Lööw, J. (2020). Attractive work and ergonomics: Designing attractive work systems. *Theoretical Issues in Ergonomics Science*, *21*(4), 442–462. https://doi.org/10.1080/1463922X.2019.1694728

López, A. (2021, March 12). *Aerospace industry employment Mexico 2020*. Statista. https://www.statista.com/statistics/892755/mexico-aerospace-employment-share-age/

Lueg, K. (2018). Organizational changes towards a European academic field. A case study of frictions in the narratives of Europeanization at a German university from an institutional perspective. *Innovation: The European Journal of Social Science Research*, *31*(4), 484–503. https://doi.org/10.1080/13511610.2018.1490637

Lumen Learning. (n.d.). *Mathematics for the liberal arts: Module 5: Fractals: Fractal basics*. Retrieved January 27, 2021, from https://courses.lumenlearning.com/wmopen-mathforliberalarts/chapter/introduction-fractal-basics/

Lund Research. (2013). *Pearson's product-moment correlation*. Laerd Statistics. https://statistics.laerd.com/premium/spss/pc/pearson-correlation-in-spss-3.php#basic-requirements

Lundahl, T., Ohley, W. J., Kay, S. M., & Siffert, R. (1986). Fractional Brownian motion: A maximum likelihood estimator and its application to image texture. *IEEE Transactions on Medical Imaging*, *5*(3), 152–161. https://doi.org/10.1109/TMI.1986.4307764

Malik, P. (2015). *The fractal organization: Creating enterprises of tomorrow*. SAGE Publications.

Mandelbrot, B. B. (1982). *The fractal geometry of nature* (Vol. 1). W. H. Freeman.

Manson, S. M. (2001). Simplifying complexity: A review of complexity theory. *Geoforum*, *32*(3), 405–414. https://doi.org/10.1016/S0016-7185(00)00035-X

Mansour, S. B., Jouini, E., & Napp, C. (2006). Is there a "pessimistic" bias in individual beliefs? Evidence from a simple survey. *Theory and Decision*, *61*(4), 345–362.

https://doi.org/10.1007/s11238-006-9014-2

Marczyk, G., DeMatteo, D., & Festinger, D. (2005). *Essentials of research design and methodology*. John Wiley & Sons.

Marinescu, R., Seceleanu, C., Le Guen, H., & Pettersson, P. (2015). A research overview of tool-supported model-based testing of requirements-based designs. In A. R. Hurson (Ed.), *Advances in computers* (Vol. 98, pp. 89–140). Elsevier. https://doi.org/10.1016/bs.adcom.2015.03.003

Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural Equation Modeling*, *11*(3), 320–341. https://doi.org/10.1207/s15328007sem1103_2

Marshak, R. J., & Bushe, G. R. (2022). A compelling beginning and more to uncover. *Journal of Applied Behavioral Science*, *58*(1), 149–152. https://doi.org/10.1177/00218863211060884

Masuyama, Y., Funo, K., Murashita, Y., Noguchi, A., Kono, S., Tabuchi, Y., Yamazaki, R., Ueda, M., & Nakamura, Y. (2018). Information-to-work conversion by Maxwell's demon in a superconducting circuit quantum electrodynamical system. *Nature Communications*, *9*(1), Article 1291. https://doi.org/10.1038/s41467-018-03686-y

Mazri, C. (2021). "You don't manage what you don't measure" ... But do you really manage what you measure? *Chemical Engineering Transactions*, *86*, 361–366. https://doi.org/10.3303/CET2186061

McCoy, M. G. (2022). Aerospace industry in U.S. In *Salem Press encyclopedia.* Salem Press. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=ers&AN=89876829&site=eds-live&scope=site

McCrie, R. (2016). Core competencies to create effective protection programs. In *Security operations management* (3rd ed., pp. 37–68). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-12-802396-9.00002-5

McDonald, D. R. (2021). Questionnaires and interviews in survey research. In *Salem Press encyclopedia of health*. Salem Press. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=ers&AN=93872191&site=eds-live&scope=site.

McLeod, S. A. (2019, June 10). *What are confidence intervals in statistics?* Simply Psychology. https://www.simplypsychology.org/confidence-interval.html

Mendez, J., & Vila-Alonso, M. (2018). Three-dimensional sustainability of Kaizen. *TQM Journal*, *30*(4), 391–408. https://doi.org/10.1108/TQM-12-2017-0179

Mentore, L. (2012). The intersubjective life of Cassava among the Waiwai. *Anthropology and Humanism*, *37*(2), 146–155. https://doi.org/10.1111/j.1548-1409.2012.01125.x

Merriam-Webster. (n.d.). Stochastic. In *Merriam-Webster.com dictionary*. Retrieved July 10, 2021, from https://www.merriam-webster.com/dictionary/stochastic

Meske, C., Kissmer, T., & Stieglitz, S. (2020). Bridging formal barriers in digital work environments – Investigating technology-enabled interactions across organizational hierarchies. *Telematics and Informatics*, *48*, Article 101342. https://doi.org/10.1016/j.tele.2020.101342

Meunier, D. (2008). Thinking relationality: Keeping the conceptual framework and the fieldwork flowing. *Conference Papers -- International Communication Association*, 1. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=edo&AN=36957041&site=eds-live&scope=site

Miake-Lye, I. M., Delevan, D. M., Ganz, D. A., Mittman, B. S., & Finley, E. P. (2020). Unpacking organizational readiness for change: An updated systematic review and content analysis of assessments. *BMC Health Services Research*, *20*(1), Article 106. https://doi.org/10.1186/s12913-020-4926-z

Michael, M. (2017). *Actor-network theory: Trials, trails and translations*. SAGE Publications.

Minitab 18 Support. (n.d.). *Understanding test for equal variances*. Retrieved March 13, 2022, from https://support.minitab.com/en-us/minitab/18/help-and-how-to/modeling-statistics/anova/supporting-topics/basics/understanding-test-for-equal-variances/

Minitab Express Support. (n.d.). *A comparison of the Pearson and Spearman correlation methods*. Retrieved Jan 14, 2022 from https://support.minitab.com/en-us/minitab-express/1/help-and-how-to/modeling-statistics/regression/supporting-topics/basics/a-comparison-of-the-pearson-and-spearman-correlation-methods/

Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019).

Descriptive statistics and normality tests for statistical data. *Annals of cardiac anaesthesia*, *22*(1), 67–72. https://doi.org/10.4103/aca.ACA_157_18

Mitić, V. V., Lazović, G. M., Manojlović, J. Ž., Huang, W.-C., Stojiljković, M. M., Facht, H., & Vlahović, B. (2020). Entropy and fractal nature. *Thermal Science*, *24*(3B), 2203–2212. https://doi.org/10.2298/TSCI191007451M

Mollenhauer, B. (2017). Chaos theory and fractals. *Australian Orthoptic Journal*, *49*, 9–21. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=a9h&AN=121942112&site=eds-live&scope=site

Mosteanu, N. R., Facia, A., Torrebruno, G., & Torrebruno, F. (2019). Fractals – A smart financial tool to assess business management decisions. *Journal of Information Systems & Operations Management*, *13*(1), 45–56. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=edb&AN=136407226&site=eds-live&scope=site

Musgrove, C. (Casey) F., Ellinger, A. E., & Ellinger, A. D. (2014). Examining the influence of strategic profit emphases on employee engagement and service climate. *Journal of Workplace Learning*, *26*(3–4), 152–171. https://doi.org/10.1108/JWL-08-2013-0057

Nafis, S. R., Alluri, P., Wu, W., & Kibria, B. M. G. (2021). Wrong-way driving crash injury analysis on arterial road networks using non-parametric data mining techniques. *Journal of Transportation Safety & Security*. Advance online publication. https://doi.org/10.1080/19439962.2021.1960660

Naikar, N., & Elix, B. (2021). Designing for self-organisation in sociotechnical systems: Resilience engineering, cognitive work analysis, and the diagram of work organisation possibilities. *Cognition, Technology & Work*, *23*(1), 23–37. https://doi.org/10.1007/s10111-019-00595-y

Naslund, D., & Norrman, A. (2019). A performance measurement system for change initiatives: An action research study from design to evaluation. *Business Process Management Journal*, *25*(7), 1647–1672. https://doi.org/10.1108/BPMJ-11-2017-0309

Nespeca, V., Comes, T., Meesters, K., & Brazier, F. (2020). Towards coordinated self-organization: An actor-centered framework for the design of disaster management information systems. *International Journal of Disaster Risk Reduction*, *51*, Article 101887. https://doi.org/10.1016/j.ijdrr.2020.101887

Newson, R. (2002). Parameters behind "nonparametric" statistics: Kendall's tau, Somers' D and median differences. *The Stata Journal*, *2*(1), 45–64. https://doi.org/10.1177/1536867X0200200103

Nielsen, C., & Lund, M. (2018). Building scalable business models. *MIT Sloan Management Review*, *59*(2), 65–69. https://www.proquest.com/scholarly-journals/building-scalable-business-models/docview/1986317543/se-2?accountid=14872

Nonaka, I., Kodama, M., Hirose, A., & Kohlbacher, F. (2014). Dynamic fractal organizations for promoting knowledge-based transformation – A new paradigm for organizational theory. *European Management Journal*, *32*(1), 137–146.

https://doi.org/10.1016/j.emj.2013.02.003

Norcross, J. C., Krebs, P. M., & Prochaska, J. O. (2011). Stages of change. *Journal of Clinical Psychology*, *67*(2), 143–154. https://doi.org/10.1002/jclp.20758

Nuhfer, E. (2017). Welcoming the other butterflies: Improving learning through respect and gratitude, educating in fractal patterns XLVIIII. *The National Teaching & Learning Forum*, *26*(5), 9–11. https://doi.org/10.1002/ntlf.30124

Nye, C. D., Brummel, B. J., & Drasgow, F. (2010). Too good to be true? Understanding change in organizational outcomes. *Journal of Management*, *36*(6), 1555–1577. https://doi.org/10.1177/0149206310376326

Ojo, O., Ojo, O. D., & Onewo, T. (2020). Relationship between profit after tax and corporate social responsibility expenditure in selected banks and manufacturing firms in Nigeria. *Хабаршысы. Экономика Сериясы*, *134*(4), 34–43. https://doi.org/10.26577/be.2020.v134.i4.03

Onwuegbuzie, A. J. (2000, November 21). *Expanding the framework of internal and external validity in quantitative research* [Paper presentation]. Annual Meeting of the Association for the Advancement of Educational Research (AAER), Ponte Vedra, FL, United States. https://files.eric.ed.gov/fulltext/ED448205.pdf

Panja, S., & James, A. P. (2020). Belief index for fake COVID19 text detection. In *2020 IEEE Recent Advances in Intelligent Computational Systems (RAICS)* (pp. 63–67). IEEE. https://doi.org/10.1109/RAICS51191.2020.9332508

Parke, M. R., Tangirala, S., & Hussain, I. (2021). Creating organizational citizens: How and when supervisor- versus peer-led role interventions change organizational citizenship behavior. *Journal of Applied Psychology*, *106*(11), 1714–1733. https://doi.org/10.1037/apl0000848

Perl, E. J., & Noldon, D. F. (2000). Overview of student affairs research methods: Qualitative and quantitative. *New Directions for Institutional Research*, (108), 37–48. https://doi.org/10.1002/ir.10803

Pervukhina, S., & Lysova, O. (2021). Ways of text adaptation by means of creolization in pedagogical discourse. *E3S Web of Conferences*, *273*, Article 12162. https://doi.org/10.1051/e3sconf/202127312162

Petursdottir, A. I., & Carr, J. E. (2018). Applying the taxonomy of validity threats from mainstream research design to single-case experiments in applied behavior analysis. *Behavior Analysis in Practice*, *11*(3), 228–240. https://doi.org/10.1007/s40617-018-00294-6

Pfaff, E. R., Champion, J., Bradford, R. L., Clark, M., Xu, H., Fecho, K., Krishnamurthy, A., Cox, S., Chute, C. G., Overby Taylor, C., & Ahalt, S. (2019). Fast healthcare interoperability resources (FHIR) as a meta model to integrate common data models: Development of a tool and quantitative validation study. *JMIR Medical Informatics*, *7*(4), Article e15199. https://doi.org/10.2196/15199

Phillips, A. W. (2017). Proper application of surveys as a study methodology. *Western Journal of Emergency Medicine: Integrating Emergency Care with Population Health*, *18*(1), 8–11. https://doi.org/10.5811/westjem.2016.11.32000

Pianesi, A. (2019). Design thinking plus adaptive leadership: Leading organizational change with the Change Canvas. *Organization Development Journal*, *37*(3), 45–

58.
https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=bth&AN=139880354&site=eds-live&scope=site

Pihlak, Ü., & Alas, R. (2012). Leadership style and employee involvement during organizational change. *Journal of Management & Change*, *29*(1), 46–66. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=bth&AN=87529153&site=eds-live&scope=site.

Pilgrim, C., Guo, W., & Johnson, S. (2020). Organisational social influence on directed hierarchical graphs, from tyranny to anarchy. *Scientific Reports*, *10*(1), Article 4388. https://doi.org/10.1038/s41598-020-61196-8

Pîslă, A., & Muntean, R. (2010). Consideraţii Privind structuri în reprezentarea modelului fractal în unităţile de producţie [Consideration of structures in the representation of fractal patterns within the production units]. *Review of Management & Economic Engineering*, *9*(1), 65–74. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=bth&AN=48921884&site=eds-live&scope=site

Pold, J., & Ivie, R. (2019). *Workforce Survey of 2018 US AAS Members Summary Results*. AAS.org. https://aas.org/sites/default/files/2019-10/AAS-Members-Workforce-Survey-final.pdf

Pollatsek, A., & Well, A. D. (1995). On the use of counterbalanced designs in cognitive research: A suggestion for a better and more powerful analysis. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *21*(3), 785–794.

https://doi.org/10.1037/0278-7393.21.3.785

Powell, T. C. (2020). Can quantitative research solve social problems? Pragmatism and the ethics of social research. *Journal of Business Ethics*, *167*(1), 41–48. https://doi.org/10.1007/s10551-019-04196-7

Prochaska, J. O., Norcross, J. C., & Saul, S. F. (2020). Generating psychotherapy breakthroughs: Transtheoretical strategies from population health psychology. *American Psychologist*, *75*(7), 996–1010. https://doi.org/10.1037/amp0000568

Price, R. K. (2012). Epidemiology. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf, & K. J. Sher (Eds.), *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological.* (pp. 253–274). American Psychological Association. https://doi.org/10.1037/13620-015

Pryor, R. G. L., & Bright, J. E. H. (2014). The chaos theory of careers (CTC): Ten years on and only just begun. *Australian Journal of Career Development*, *23*(1), 4–12. https://doi.org/10.1177/1038416213518506

Qiu, J.-H., Soubeyran, A., & He, F. (2020). Equilibrium versions of set-valued variational principles and their applications to organizational behavior. *Optimization*, *69*(12), 2657–2693. https://doi.org/10.1080/02331934.2020.1718127

Rafferty, A. E., & Minbashian, A. (2019). Cognitive beliefs and positive emotions about change: Relationships with employee change readiness and change-supportive behaviors. *Human Relations*, *72*(10), 1623–1650. https://doi.org/10.1177/0018726718809154

Ramirez, R., Bhatti, Y., & Tapinos, E. (2020). Exploring how experience and learning curves decrease the time invested in scenario planning interventions. *Technological Forecasting and Social Change*, *151*, Article 119785. https://doi.org/10.1016/j.techfore.2019.119785

Ravitch, S. M., & Carl, N. M. (2019). *Qualitative research: Bridging the conceptual, theoretical, and methodological*. SAGE Publications.

Rea, L. M., & Parker, R. A. (2014). *Designing and conducting survey research: A comprehensive guide* (4th ed.). Jossey-Bass.

Reeping, D., Grote, D. M., & Knight, D. B. (2021). Effects of large-scale programmatic change on electrical and computer engineering transfer student pathways. *IEEE Transactions on Education*, *64*(2), 117–123. https://doi.org/10.1109/TE.2020.3015090

Reichardt, C. S. (2009). Quasi-experimental design. In R. E. Millsap, & A. Maydeu-Olivares (Eds.), *The SAGE handbook of quantitative methods in psychology* (pp. 47–72). SAGE Publications. https://doi.org/10.4135/9780857020994.n3

Rijgersberg, H., Top, J., & Meinders, M. (2009). Semantic support for quantitative research processes. *IEEE Intelligent Systems*, *24*(1), 37–46. https://doi.org/10.1109/MIS.2009.17

Robitzsch, A. (2020). Why Ordinal variables can (almost) always be treated as continuous variables: Clarifying assumptions of robust continuous and ordinal factor analysis estimation methods. *Frontiers in Education*, *5*. https://doi.org/10.3389/feduc.2020.589965

Rose, R. A., & Fraser, M. W. (2008). A simplified framework for using multiple imputation in social work research. *Social Work Research*, *32*(3), 171–178. https://doi.org/10.1093/swr/32.3.171

Ruben, B. D., & Gigliotti, R. A. (2021). Explaining incongruities between leadership theory and practice: Integrating theories of resonance, communication and systems. *Leadership & Organization Development Journal*, *42*(6), 942–957. https://doi.org/10.1108/LODJ-02-2021-0072

Rumahlewang, E., Latar, I. M., & Siang, J. L. (2021). The influence of scientific attitude and emotional intelligence on learning outcomes of research methodology for FKIP Unpatti Ambonese Students. *Review of International Geographical Education*, *11*(2), 1–11. http://www.rigeo.org/vol10no2/Number2Spring/RIGEOV10-N2-1.pdf

Ryan, S. (2016, November 25). How loss aversion and conformity threaten organizational change. *Harvard Business Review*. https://hbr.org/2016/11/how-loss-aversion-and-conformity-threaten-organizational-change

Samba, C., Tabesh, P., Thanos, I. C., & Papadakis, V. M. (2021). Method in the madness? A meta-analysis on the strategic implications of decision comprehensiveness. *Strategic Organization*, *19*(3), 414–440. https://doi.org/10.1177/1476127020904973

Sander, C. (2017). Construction zone: Europe from the perspective of change management. *The European Legacy*, *22*(7–8), 789–796. https://doi.org/10.1080/10848770.2017.1368784

Santucci, A. C. (2021). Data description in research. In *Salem Press encyclopedia of health*. Salem Press. https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=ers&AN=93871877&site=eds-live&scope=site.

Sari, B. G., Lúcio, A. D., Santana, C. S., Krysczun, D. K., Tischler, A. L., & Drebes, L. (2017). Sample size for estimation of the Pearson correlation coefficient in cherry tomato tests. *Ciência Rural*, *47*(10). https://doi.org/10.1590/0103-8478cr20170116

Sarkies, M. N., Skinner, E. H., Bowles, K.-A., Morris, M. E., Williams, C., O'Brien, L., Bardoel, A., Martin, J., Holland, A. E., Carey, L., White, J., & Haines, T. P. (2019). A novel counterbalanced implementation study design: Methodological description and application to implementation research. *Implementation Science*, *14*(1), Article 45. https://doi.org/10.1186/s13012-019-0896-0

Schirmer, F., & Geithner, S. (2018). Power relations in organizational change: An activity-theoretic perspective. *Journal of Accounting & Organizational Change*, *14*(1), 9–32. https://doi.org/10.1108/JAOC-11-2016-0074

Schiuma, G., Mason, S., & Kennerley, M. (2007). Assessing energy within organisations. *Measuring Business Excellence*, *11*(3), 69–78. https://doi.org/10.1108/13683040710820764

Schowengerdt, R. A. (2006). *Remote sensing: Models and methods for image processing* (3rd ed.). Elsevier.

Schroeders, U., Schmidt, C., & Gnambs, T. (2021). Detecting careless responding in survey data using stochastic gradient boosting. *Educational and Psychological Measurement*, *82*(1), 29–56. https://doi.org/10.1177/00131644211004708

Schwarz, G. M., Bouckenooghe, D., & Vakola, M. (2021). Organizational change failure: Framing the process of failing. *Human Relations*, *74*(2), 159–179. https://doi.org/10.1177/0018726720942297

Schweiger, S., Stouten, H., & Bleijenbergh, I. L. (2018). A system dynamics model of resistance to organizational change: The role of participatory strategies. *Systems Research and Behavioral Science*, *35*(6), 658–674. https://doi.org/10.1002/sres.2509

Senge, P., Schneider, F., & Wallace, D. (2014). Peter Senge on the 25th anniversary of *The Fifth Discipline*. *Reflections*, *14*(3). https://eds.s.ebscohost.com/eds/pdfviewer/pdfviewer?vid=8&sid=b0baf495-83d9-49a3-8da0-36aaf1f98e9a%40redis

Sharma, H. (2021). Statistical significance or clinical significance? A researcher's dilemma for appropriate interpretation of research results. *Saudi Journal of Anaesthesia*, *15*(4), 431–434. https://doi.org/10.4103/sja.sja_158_21

Shi, G. (2013). *Data mining and knowledge discovery for geoscientists*. Elsevier.

Sibbet, D. (2013). *Visual leaders: New tools for visioning, management, and organization change*. John Wiley & Sons. https://www.wiley.com/en-us/Visual+Leaders%3A+New+Tools+for+Visioning%2C+Management%2C+and+Organization+Change-p-9781118494226

Silva, A. L., & Guerrini, F. M. (2018). Self-organized innovation networks from the perspective of complex systems: A comprehensive conceptual review. *Journal of Organizational Change Management*, *31*(5), 962–983. https://doi.org/10.1108/JOCM-10-2016-0210

Silvia, P. J., & Cotter, K. N. (2021). Cleaning and processing your data. In P. J. Silvia & K. N. Cotter (Eds.), *Researching daily life: A guide to experience sampling and daily diary methods* (pp. 93–109). American Psychological Association. https://doi.org/10.1037/0000236-006

Slevitch, L. (2011). Qualitative and quantitative methodologies compared: Ontological and epistemological perspectives. *Journal of Quality Assurance in Hospitality & Tourism*, *12*(1), 73–81. https://doi.org/10.1080/1528008X.2011.541810

Smith, J. D., Rafferty, M. R., Heinemann, A. W., Meachum, M. K., Villamar, J., Lieber, R. L., & Brown, C. H. (2020). Pragmatic adaptation of implementation research measures for a novel context and multiple professional roles: A factor analysis study. *BMC Health Services Research*, *20*(1), Article 257. https://doi.org/10.1186/s12913-020-05118-4

Sorge, A., & van Witteloostuijn, A. (2004). The (non)sense of organizational change: An essai about universal management hypes, sick consultancy metaphors, and healthy organization theories. *Organization Studies*, *25*(7), 1205–1231. https://doi.org/10.1177/0170840604046360

Sovacool, B. K., & Hess, D. J. (2017). Ordering theories: Typologies and conceptual frameworks for sociotechnical change. *Social Studies of Science*, *47*(5), 703–750. https://doi.org/10.1177/0306312717709363

Spaulding, A., Kash, B. A., Johnson, C. E., & Gamm, L. (2017). Organizational capacity for change in health care: Development and validation of a scale. *Health Care Management Review*, *42*(2), 151–161. https://doi.org/10.1097/HMR.0000000000000096

Stame, N. (2010). What doesn't work? Three failures, many answers. *Evaluation*, *16*(4), 371–387. https://doi.org/10.1177/1356389010381914

Stasulane, A. (2021). Identity multiplicity in an ethnic and religious minority in Latvia: Old believer youth. *Frontiers in Sociology*, *6*, Article 641622. https://doi.org/10.3389/fsoc.2021.641622

Steghofer, J.-P. (2017). Change is afoot: Applying change management theories to self-organizing socio-technical systems. *IEEE Technology and Society Magazine*, *36*(3), 56–62. https://doi.org/10.1109/MTS.2017.2728735

Stickl Haugen, J., Sutter, C. C., Tinstman Jones, J. L., & Campbell, L. O. (2021). The teacher expectations and values for suicide prevention scale: Confirmatory factor analysis and validation. *Crisis*, *42*(3), 186–193. https://doi.org/10.1027/0227-5910/a000706

Stone, K. B. (2010). Kaizen teams: Integrated HRD practices for successful team building. *Advances in Developing Human Resources*, *12*(1), 61–77. https://doi.org/10.1177/1523422310365333

Suárez-Colorado, Y. P., Caballero-Domínguez, C. C., & Campo-Arias, A. (2022). Confirmatory factor analysis and internal consistency of the suicidal ideation scale of the center for epidemiological studies depression among Colombian adolescents. *Psychological Reports*, *125*(1), 588–598. https://doi.org/10.1177/0033294120971771

Sullivan, G. M. (2011). A primer on the validity of assessment instruments. *Journal of Graduate Medical Education*, *3*(2), 119–120. https://doi.org/10.4300/JGME-D-11-00075.1

Sullivan, M. C., & Wegman, E. J. (1995). Correlation estimators based on simple nonlinear transformations. *IEEE Transactions on Signal Processing*, *43*(6), 1438–1444. https://doi.org/10.1109/78.388856

Sune, A., & Gibb, J. (2015). Dynamic capabilities as patterns of organizational change: An empirical study on transforming a firm's resource base. *Journal of Organizational Change Management*, *28*(2), 213–231. https://doi.org/10.1108/JOCM-01-2015-0019

Szamosi, L. T., & Duxbury, L. (2002). Development of a measure to assess organizational change. *Journal of Organizational Change Management*, *15*(2), 184–201. https://doi.org/10.1108/09534810210423107

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, *48*(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Tao, Y. (2017). Quantum behavior arises because our universe is a fractal. *Reports in Advances of Physical Sciences*, *1*(2). https://doi.org/10.1142/S2424942417500062

Tasselli, S., & Caimo, A. (2019). Does it take three to dance the tango? Organizational design, triadic structures and boundary spanning across subunits. *Social Networks*, *59*, 10–22. https://doi.org/10.1016/j.socnet.2019.04.002

Tawodzera, M. C., Mabasa, L. T., & Themane, M. (2022). Contributions of social research methodologies to social change: Giving voice to the voiceless. *International Journal of Qualitative Methods*, 1–7. https://doi.org/10.1177/16094069211072417

Trochim, W. M. K. (n.d.). *Quasi-experimental design*. Conjoint.ly. Retrieved March 21, 2021, from https://conjointly.com/kb/quasi-experimental-design/

Tronvoll, B., Sklyar, A., Sörhammar, D., & Kowalkowski, C. (2020). Transformational shifts through digital servitization. *Industrial Marketing Management*, *89*, 293–305. https://doi.org/10.1016/j.indmarman.2020.02.005

Uka, A., & Prendi, A. (2021). Motivation as an indicator of performance and productivity from the perspective of employees. *Management & Marketing*, *16*(3), 268–285. https://doi.org/10.2478/mmcks-2021-0016

United Nations Department of Economic and Social Affairs, Population Division. (2020). *World Population Ageing 2019* [Report]. https://www.un.org/en/development/desa/population/publications/pdf/ageing/WorldPopulationAgeing2019-Report.pdf

USA.Gov. (2018). *Aerospace spotlight*. Retrieved April 5, 2021, from http://www.behlives.com/selectusa/aerospace-industry-united-states/#

Vakili, M. (2018). Systems philosophy. *Cosmos and History: The Journal of Natural and Social Philosophy*, *14*(1), 203–216. https://cosmosandhistory.org/index.php/journal/article/view/695

Voss, R. A., Krumwiede, D. W., & Lucas, A. D. (2017). Fractality in four dimensions: A framework for understanding organizations as fractal entities. *International Journal of the Academic Business World*, *11*(2). : https://www.researchgate.net/publication/356591968

Wang, S.-T., Yu, M.-L., Wang, C.-J., & Huang, C.-C. (1999). Bridging the gap between the pros and cons in treating ordinal scales as interval scales from an analysis point of view. *Nursing Research*, *48*(4), 226–229. https://doi.org/10.1097/00006199-199907000-00006

Warner, R. M. (2012). *Applied statistics: From bivariate through multivariate techniques* (2nd ed.). SAGE Publications.

Wasserman, J. A., & Clair, J. M. (2011). The medicalization of homelessness and the sociology of the self: A grounded fractal analysis. In *Studies in symbolic interaction*. Emerald Group Publishing Limited. https://doi.org/10.1108/S0163-2396(2011)0000037004

Watad, M. (2019). Organizational learning and change: Can they coexist? *Business Process Management Journal*, *25*(5), 1070–1084. https://doi.org/10.1108/BPMJ-12-2016-0240

Weber, G. F. (2019). Information gain in event space reflects chance and necessity components of an event. *Information*, *10*(11), Article 358. https://doi.org/10.3390/info10110358

Webster, J. (2016). Creolization. In *Oxford classical dictionary.* Oxford University Press. https://doi.org/10.1093/acrefore/9780199381135.013.6981

Wells, R. S., & Stage, F. K. (2015). Past, present, and future of critical quantitative research in higher education. *New Directions for Institutional Research*, (163), 103–112. https://doi.org/10.1002/ir.20089

Westbroek, J., Nijhuis, H., & van der Maesen, L. (2020). Evolutionary thermodynamics and theory of social quality as links between physics, biology, and the human sciences. *International Journal of Social Quality*, *10*(1), 57–86. https://doi.org/10.3167/IJSQ.2020.100104

Whitley, E., & Ball, J. (2002). Statistics review 6: Nonparametric methods. *Critical Care*, (6), Article 509. https://doi.org/10.1186/cc1820

Wilcox, R. R. (2022). Comparing two groups. In *Introduction to robust estimation and hypothesis testing* (5th ed., pp. 153–251). Academic Press. https://doi.org/10.1016/B978-0-12-820098-8.00011-7

Wong, C. S., Chu, W., Ashamalla, S., Fenech, D., Berry, S., Kiss, A., & Koritzinsky, M. (2021). Metformin with neoadjuvant chemoradiation to improve pathologic response in rectal cancer: A pilot phase I/II trial. *Clinical and Translational Radiation Oncology*, *30*, 60–64. https://doi.org/10.1016/j.ctro.2021.07.001

Wu, H., & Leung, S.-O. (2017). Can Likert scales be treated as interval scales?—A simulation study. *Journal of Social Service Research*, *43*(4), 527–532. https://doi.org/10.1080/01488376.2017.1329775

Yaffe, M. J., & Boyd, N. F. (2009). Quantitative image analysis for estimation of breast cancer risk. In I. N. Bankman (Ed.), *Handbook of medical image processing and analysis* (2nd ed., pp. 381–398). Academic Press. https://doi.org/10.1016/B978-

012373904-9.50032-5

Yedidia, J. S., Freeman, W. T., & Weiss, Y. (2005). Constructing free-energy approximations and generalized belief propagation algorithms. *IEEE Transactions on Information Theory*, *51*(7), 2282–2312. https://doi.org/10.1109/TIT.2005.850085

Yin, Y., Wang, S., & Zhou, J. (2022). Complex network–based change propagation path optimization in mechanical product development. *IEEE Access*, *10*, 17389–17399. https://doi.org/10.1109/ACCESS.2022.3149001

Zelt, S., Recker, J., Schmiedel, T., & vom Brocke, J. (2018). Development and validation of an instrument to measure and manage organizational process variety. *PLoS ONE*, *13*(10), Article e0206198. https://doi.org/10.1371/journal.pone.0206198

Zhang, M. F., Dawson, J. F., & Kline, R. B. (2021). Evaluating the use of covariance-based structural equation modelling with reflective measurement in organizational and management research: A review and recommendations for best practice. *British Journal of Management*, *32*(2), 257–272. https://doi.org/10.1111/1467-8551.12415

Zimmermann, B. (2018). From critical theory to critical pragmatism: Capability and the assessment of freedom. *Critical Sociology*, *44*(6), 937–952. https://doi.org/10.1177/0896920517691107

Žužek, T., Kušar, J., Rihar, L., & Berlec, T. (2020). Agile-concurrent hybrid: A framework for concurrent product development using Scrum. *Concurrent Engineering*, *28*(4), 255–264. https://doi.org/10.1177/1063293X20958541

Zyphur, M. J., & Pierides, D. C. (2020). Statistics and probability have always been value-laden: An historical ontology of quantitative research methods. *Journal of Business Ethics*, *167*(1), 1–18. https://doi.org/10.1007/s10551-019-04187-8

Appendix A: Fractal Emergence Survey Questions

Fracatal Emergence in Organizational Change Survey: Modifications of Original Questions to suit OC context

Source:	Dimension or Category	Original Question as Written	Modified Question to support Fractal Emergence	Rationale for the change
Ai, et al (2019)	**Identity Multiplicity (IM)**	IM1 - There is little cultural difference in this organization betweeh the Chinese and foreign employees	IM1 - In general Managers and workers share similar values in this company	Tailored to look at hierarchical view, culture translated to value, which makes up company culture
		IM2 - In this company, Chinese and foreign employees have similar values	IM2 - I believe that my manager's commitment to the change initiative and mine (are/were) similar.	Tailored to specifically address commitment to the change based on leader/follower
		IM3 - Chinese and Foreign employees in this organization interact on an equal basis	IM3 - Managers and employees in this company tend to interact on an equal basis.	Substitute specific case used by authors for generic OC hierarchical interaction
		IM4 - I Mainly identify with the values of the country I originate from	IM4 - I think the goal of the change my company envisioned (moves/moved) us closer to our core values and who we want to be as a company.	Substiture country values to OC change and company values
Ai, et al (2019)	**Cultural Hybridity**	CH1 - In the project team, we adopt some of the client's organizational practices, culture and regulation	CH1 - In project teams, we (have changed or have started to change) our organizational practices because of the change initiative.	Tailored to adjust for OC instead of specific case of KMS used by authors
		CH2- In the project team, we adopt mixed cultural practice from both countries	CH2 - I believe my colleagues and I (have changed or are very likely to change) the way we work to align with the goals of the change initiative	Assess cultural change as a function of OC behavioral change
		CH3- In the project team, the client's cultrual practices are dominant in our organization	CH3 - In my day-to-day work, I have changed the way I (behave/behaved) as a result of the change initiative.	Personalize the practice to the individual level in OC
Ai, et al (2019)	**Boundary Spanning**	BS1 - Some team memgers fisit the client's site to improve understanding of client's organizational practices, ethnic backgrounds and product development	BS1 - My immediate manager and I (discuss/discussed) how to best implement change.	Change client/team to hierarchical interaction and sense-making
		BS2- One or more team members who have visited client's site are able to share knowledge gained with other team members	BS2 - One or more of my colleagues or coworkers routinely (discuss/discussed) the change initiative.	Change client/team to peer and team level interaction and sense-making
		BS3 - One or more team members had been formally designated to facilitated coordination with the client and with regard to cultural issues	BS3 - One or more of my peers or colleagues (has been/was) formally or informally designated to help my group reach its goals with respect to the desired change.	Establish whether leaders emerge as part of the OC process
		BS4 - One or more team members had been informally designated to facilitate coordinaation with client regarding cultrual issues	BS4 - One or more members of our senior management team (have/had) training in the change process or (has/had) experience implementing this kind of change.	Assess the view of upper management as participatory in the OC process
Ai, et al (2019)	**Network Expansion**	NE1 - One or more members of our senior management team have multi-cultural backgrounds and/or experience relevant to the foreign client	NE1 - I believe that our senior management (considered/considers) the change worth the effort and (believes/believed) that the change will improve the company performance in the long run.	Assess whether others view that upper management is committed to the change
		NE2- One or more members of our senior management team perform a liason or bridging role with regard to the foreign client	NE2 - One or more members of the senior management team (was/are) capable of helping me achieve the goals of the change initiative.	Assess whether others percieve upper management as capable of helping/teaming
		NE3 - One or more members of the senior management team are capable of setting up connections with both onshore and offshore business contacts and generate business opportunities	NE3 - I think that other groups within my company (adopted/are adopting) the change well.	The original question was too geograohically situate, the new question looks across hierarchical boundaries

Fracatal Emergence in Organizational Change Survey: Modifications of Original Questions to suit OC context				
Source:	**Dimension or Category**	**Original Question as Written**	**Modified Question to support Fractal Emergence**	**Rationale for the change**
Li,Liu, & Liu (2016)	**Loss Aversion**	LA1 - My current way of managing knowledge provides me particular privileges that I would not receive if I were to switch to the new way of working with the KMS.	LA1 - Before the change, my previous way of working gave advantages or privileges that I (did not / would not) receive compared to the new way of working.	Minor wording change to make question relevant to OC inquiry
		LA2 - My competitive advantage in the workplace would diminish if I were to switch to the new way of working with the KMS.	LA2 - Before the change, my previous way of working was more effective and (was/would be) reduced if I were to switch to the new way of working.	Minor wording change to make question relevant to OC inquiry
Li,Liu, & Liu (2016)	**Transaction Costs**	TC1 - It would take a lot of time and effort to switch to the new way of working with KMS.	TC1 - It (did/would) take a lot of time and effort to switch to the new way of working.	Minor wording change to make question relevant to OC inquiry
		TC2 - I would lose a lot in my work if I were to switch to the new way of working with KMS.	TC2 - I (did/would) lose a lot in my work if I were to switch to the new way of working.	Minor wording change to make question relevant to OC inquiry
		TC3 - Switching to the new way of working with KMS could result in unexpected hassles.	TC3 - Switching to the new way of working (did/could) result in unexpected hassles.	Minor wording change to make question relevant to OC inquiry
		TC4 - Learning how to use KMS to collaborate/share files with my teammates would take much time.	TC4 - Learning what I need to do differently to be aligned with the goals of the change (did/would) take much time or (was not/might not be) worth the effort.	Minor wording change to make question relevant to OC inquiry
		TC5 - Becoming skillful at using KMS to collaborate/share files with teammates would not be easy for me.	TC5 - Becoming skillful at using the new processes (was not/would not be) easy for me or my teammates.	Minor wording change to make question relevant to OC inquiry
Li,Liu, & Liu (2016)	**Social Norms**	SN1- My colleagues think I should use the KMS. [reverse-coded item]	SN1 - My colleagues think I should use the new/changed process. [reverse-coded item]	Minor wording change to make question relevant to OC inquiry
		SN2- My managers think I should use the KMS. [reverse-coded item]	SN2 - My managers think I should use the new/changed process. [reverse-coded item]	Minor wording change to make question relevant to OC inquiry
		SN3- My subordinates think I should use the KMS. [reverse-coded item]	SN3 - My subordinates think I should use the new/changed process [reverse-coded item]	Minor wording change to make question relevant to OC inquiry
Li,Liu, & Liu (2016)	**Affective Inertia**	AF1 - I [will] continue using my existing method for collaborating/sharing files with my teammates…because it would be stressful to change	AF1 -I plan on using my pre-change method for getting work done or working with my teammates…because it would be stressful to change.	Minor wording change to make question relevant to OC inquiry
		AF2 - I [will] continue using my existing method for collaborating/sharing files with my teammates… …because I am comfortable doing so.	AF2 - I plan on using my pre-change method for getting work done or working with my teammates…because I am comfortable doing so.	Minor wording change to make question relevant to OC inquiry
		AF3 - I [will] continue using my existing method for collaborating/sharing files with my teammates… because I enjoy doing so.	AF3 - I plan on using my pre-change method for getting work done or working with my teammates…because I enjoy doing so.	Minor wording change to make question relevant to OC inquiry
Li,Liu, & Liu (2016)	**Cognitive Inertia**	CI1 - I [will] continue using my existing method for collaborating/sharing files with my teammates…even though I know it is not the best way of doing things.	CI1 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the best way of doing things.	Minor wording change to make question relevant to OC inquiry
		CI2 - I [will] continue using my existing method for collaborating/sharing files with my teammates…even though I know it is not the most efficient way of doing things	CI2 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most efficient way of doing things	Minor wording change to make question relevant to OC inquiry
		CI3 - I [will] continue using my existing method for collaborating/sharing files with my teammates…even though I know it is not the most effective way to do things	CI3 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most effective way to do things.	Minor wording change to make question relevant to OC inquiry
Li,Liu, & Liu (2016)	**Resistive Intention**	RI1 - I oppose the change to the new way of working with the KMS.	RI1 - I fully support/supported the change to the new way of working.	Rephrased to capture degree of positive intent, (will capture resistance in RI 4-6)
		RI2 - I will not cooperate with the change to the new way of working with the KMS.	RI2 - I will fully cooperate/cooperated with the change to the new way of working.	Rephrased to capture degree of positive intent, (will capture resistance in RI 4-6)
		RI3 - I will not comply with the change to the new way of working with the KMS.	RI3 - I intended/intend to comply with the change to the new way of working.	Rephrased to capture degree of positive intent, (will capture resistance in RI 4-6)
		NA	RI4 – I (did not /do not) think the change initiative is needed.	Capture negative aspect of resistance intent
		NA	RI5 - I (did not /do not) think the initiative worked or is currently working.	Capture negative aspect of resistance intent
		NA	RI6 - I (did not /do not) think the initiative (was/will be) successful.	Capture negative aspect of resistance intent

Complete List of the Fractal Emergence Survey Questions

Change Success Information **(Prefix CS)**

CS1 - I (did not /do not) think the initiative worked or is currently working.

CS2 - I (did not /do not) think the initiative (was/will be) successful.

CS3 – Reflecting on the change process, based on what you know of what was expected of the outcome, do you think the change was successful?

CS4 - Do you believe that the change process met its goals?

Demographic Information **(Prefix DI)**

DI0-Are you a current or former aerospace employee (Y/N)?

DI1 - What is your Age in years?

DI2 - Which of the following best describes you? Please select the best answer: Asian or Pacific Islander, Black or African American, Hispanic or Latino, Native American or Alaskan Native, White or Caucasian, Multiracial or Biracial, A race or ethnicity not listed here, I prefer not to answer.

DI3-What gender do you identify as? (M/F/other/prefer not to answer)

DI4 - Number of years you have worked in this organization

DI5 - Approximately how many employees are in your organization?

DI6 - Your Level in the organization at the time of the change initiative (circle one): Worker, Manager, Senior Manager, Executive Manager

DI7 - How long did the change take to complete, or how long is it expected to take from the time it started until it is completed (in months)?

DI8 - Your estimate for the percentage complete the change process is (0-100%)

DI9 - Number of months since the organizational change was completed (0=still ongoing)

The remaining questions are designed to ascertain the factors that affect change practices using a modification of surveys provided by Ai et al. (2019) and Li et al. (2016). Table 1 lists the original source questions from the survey, the modification to the question, and the rationale for the change in phrasing of the question.

Regarding your company's current, or most recent change initiative please state the extent to which you agree with the statements given below.

(1= Strongly Disagree, 2 = Disagree, 3=Neutral, 4 = Agree, 5 = Strongly agree)

Identity Multiplicity (IM) - adapted from Ai et al. (2019)

IM1 - In general Managers and workers share similar values in this company.

IM2 - I believe that my manager's commitment to the change initiative and mine (are/were) similar.

IM3 - Managers and employees in this company tend to interact on an equal basis.

IM4 - I think the goal of the change my company envisioned (moves/moved) us closer to our core values and who we want to be as a company.

Cultural Hybridity (CH) – adapted from Ai et al. (2019)

CH1 - In project teams, we (have changed or have started to change) our organizational practices because of the change initiative.

CH2 - I believe my colleagues and I (have changed or are very likely to change) the way we work to align with the goals of the change initiative

CH3 - In my day-to-day work, I have changed the way I (behave/behaved) as a result of the change initiative.

Boundary Spanning (BS) - adapted from Ai et al. (2019)

BS1 - My immediate manager and I (discuss/discussed) how to best implement change.

BS2 - One or more of my colleagues or coworkers routinely (discuss/discussed) the change initiative.

BS3 - One or more of my peers or colleagues (has been/was) formally or informally designated to help my group reach its goals with respect to the desired change.

BS4 - One or more members of our senior management team (have/had) training in the change process or (has/had) experience implementing this kind of change.

Network Expansion (NE) - adapted from Ai et al. (2019)

NE1 - I believe that our senior management (considered/considers) the change worth the effort and (believes/believed) that the change will improve the company performance in the long run.

NE2 - One or more members of the senior management team (was/are) capable of helping me achieve the goals of the change initiative.

NE3 - I think that other groups within my company (adopted/are adopting) the change well.

The survey questions asked to this point refer to the conditions of a creolization from the old way of doing business to the new way framed by the OC. In a sense, the degree of agreement between different levels in the organization should provide a quantifiable measure of how the individuals within their hierarchical levels view the change process above and below their organizational level. However, for change to flourish, I also need a measure of intent or resistance to change. For that, I plan to assess the elements of adoption acceptance as outlined by the Li et al. (2016) survey. Specifically, I will assess loss aversion, transaction costs, Social Norms, and both Affective and Cognitive Inertial aspects of change resistance:

Loss Aversion (LA) – adapted from Li et al. (2016)

LA1 - Before the change, my previous way of working gave advantages or privileges that I (did not / would not) receive compared to the new way of working.

LA2 - Before the change, my previous way of working was more effective and (was/would be) reduced if I were to switch to the new way of working.

Transaction Costs (TC) - from Li et al. (2016)

TC1 - It (did/would) take a lot of time and effort to switch to the new way of working.

TC2 - I (did/would) lose a lot in my work if I were to switch to the new way of working.

TC3 - Switching to the new way of working (did/could) result in unexpected hassles.

TC4 - Learning what I need to do differently to be aligned with the goals of the change (did/would) take much time or (was not/might not be) worth the effort.

TC5 - Becoming skillful at using the new processes (was not/would not be) easy for me or my teammates.

Social Norms (SN) – adapted from Li et al. (2016)

SN1 - My colleagues think I should use the new/changed process. [reverse-coded item]

SN2 - My managers think I should use the new/changed process. [reverse-coded item]

SN3 - My subordinates think I should use the new/changed process [reverse-coded item]

Affective Inertia (AI) – adapted from Li et al. (2016)

AF1 -I plan on using my pre-change method for getting work done or working with my teammates…because it would be stressful to change.

AF2 - I plan on using my pre-change method for getting work done or working with my teammates…because I am comfortable doing so.

AF3 - I plan on using my pre-change method for getting work done or working with my teammates…because I enjoy doing so.

Cognitive Inertia (CI) – - adapted from Li et al. (2016)

CI1 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the best way of doing things.

CI2 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most efficient way of doing things

CI3 - I plan on using my pre-change method for getting work done or working with my teammates…even though I know it is not the most effective way to do things.

Resistive Intention (RI) – adapted from Li et al. (2016)

RI1 - I fully support/supported the change to the new way of working.

RI2 - I will fully cooperate/cooperated with the change to the new way of working.

RI3 - I intended/intend to comply with the change to the new way of working.

RI4 – I (did not /do not) think the change initiative is needed.

RI5 - I (did not /do not) think the initiative worked or is currently working.

RI6 - I (did not /do not) think the initiative (was/will be) successful.

Appendix B: Authorization to Use Survey Instruments

Copyright Clearance Center RightsLink®

Home | Help | Email Support | Thomas Seitz

Why do employees resist knowledge management systems? An empirical study from the status quo bias and inertia perspectives

Author: Jia Li,Minghui Liu,Xuan Liu
Publication: Computers in Human Behavior
Publisher: Elsevier
Date: December 2016

Order Completed

Thank you for your order.

This Agreement between Walden University -- Thomas Seitz ("You") and Elsevier ("Elsevier") consists of your license details and the terms and conditions provided by Elsevier and Copyright Clearance Center.

Your confirmation email will contain your order number for future reference.

License Number	5062311474888
License date	May 05, 2021

Printable Details

Licensed Content

Licensed Content Publisher	Elsevier
Licensed Content Publication	Computers in Human Behavior
Licensed Content Title	Why do employees resist knowledge management systems? An empirical study from the status quo bias and inertia perspectives
Licensed Content Author	Jia Li,Minghui Liu,Xuan Liu
Licensed Content Date	Dec 1, 2016
Licensed Content Volume	65
Licensed Content Issue	n/a
Licensed Content Pages	12
Journal Type	S&T

Order Details

Type of Use	reuse in a thesis/dissertation
Portion	figures/tables/illustrations
Number of figures/tables/illustrations	1
Format	electronic
Are you the author of this Elsevier article?	No
Will you be translating?	Yes, including English rights
Number of languages	1

About Your Work

Title	Fractal Properties of Organizational Change Initiatives
Institution name	Walden University
Expected presentation date	Mar 2022

Additional Data

Portions	Table 4 - Constructs and items... the authors' survey, although I will be rephrasing their questions to suit my research interest
Specific Languages	English

Requestor Location

Requestor Location	Walden University 9560 MICHAELS WAY ELLICOTT CITY, MD 21042 United States Attn: Walden University

Tax Details

Publisher Tax ID	98-0397604

$ Price

Total	0.00 USD

Total: 0.00 USD

CLOSE WINDOW

ORDER MORE

Measuring creolization in IT outsourcing: Instrument development and validation

Author: Shizhong Ai,Rong Du,Detmar W. Straub,Likoebe M. Maruping,Yumeng Miao

Publication: International Journal of Information Management

Publisher: Elsevier

Date: August 2019

Order Completed

Thank you for your order.

This Agreement between Walden University -- Thomas Seitz ("You") and Elsevier ("Elsevier") consists of your license details and the terms and conditions provided by Elsevier and Copyright Clearance Center.

Your confirmation email will contain your order number for future reference.

License Number	5063411062192
License date	May 06, 2021

Printable Details

Licensed Content

Licensed Content Publisher	Elsevier
Licensed Content Publication	International Journal of Information Management
Licensed Content Title	Measuring creolization in IT outsourcing: Instrument development and validation
Licensed Content Author	Shizhong Ai,Rong Du,Detmar W. Straub,Likoebe M. Maruping,Yumeng Miao
Licensed Content Date	Aug 1, 2019
Licensed Content Volume	47
Licensed Content Issue	n/a
Licensed Content Pages	15
Journal Type	S&T

Order Details

Type of Use	reuse in a thesis/dissertation
Portion	figures/tables/illustrations
Number of figures/tables/illustrations	1
Format	electronic
Are you the author of this Elsevier article?	No
Will you be translating?	Yes, including English rights
Number of languages	1

About Your Work

Title	Fractal Properties of Organizational Change Initiatives
Institution name	Walden University
Expected presentation date	Mar 2022

Additional Data

Portions	I plan to use Appendix A - the survey questions, however, they will be reworded to suit my organizational change topic. It is expected that the rewording will not substantially change the tool or its validity
Specific Languages	English

Requestor Location

Requestor Location	Walden University 9560 MICHAELS WAY ELLICOTT CITY, MD 21042 United States Attn: Walden University

Tax Details

Publisher Tax ID	98-0397604

Price

Total	0.00 USD

Total: 0.00 USD

CLOSE WINDOW

ORDER MORE

Appendix C: Item Analysis of Survey Themes

Item Analysis of Identity Multiplicity (IM1, IM2, IM3, IM4) Thematic Subset of Creolization

* NOTE * 123 cases used, 2 cases contain missing values

Correlation Matrix

	IM1_manvals	IM2_commit	IM3_equal
IM2_commit	0.833		
IM3_equal	0.820	0.816	
IM4_vision	0.752	0.736	0.686

Cell Contents
Pearson correlation

Covariance Matrix

	IM1_manvals	IM2_commit	IM3_equal	IM4_vision
IM1_manvals	6.8422			
IM2_commit	5.9320	7.4056		
IM3_equal	5.5488	5.7458	6.6983	
IM4_vision	5.2822	5.3817	4.7660	7.2136

Item and Total Statistics

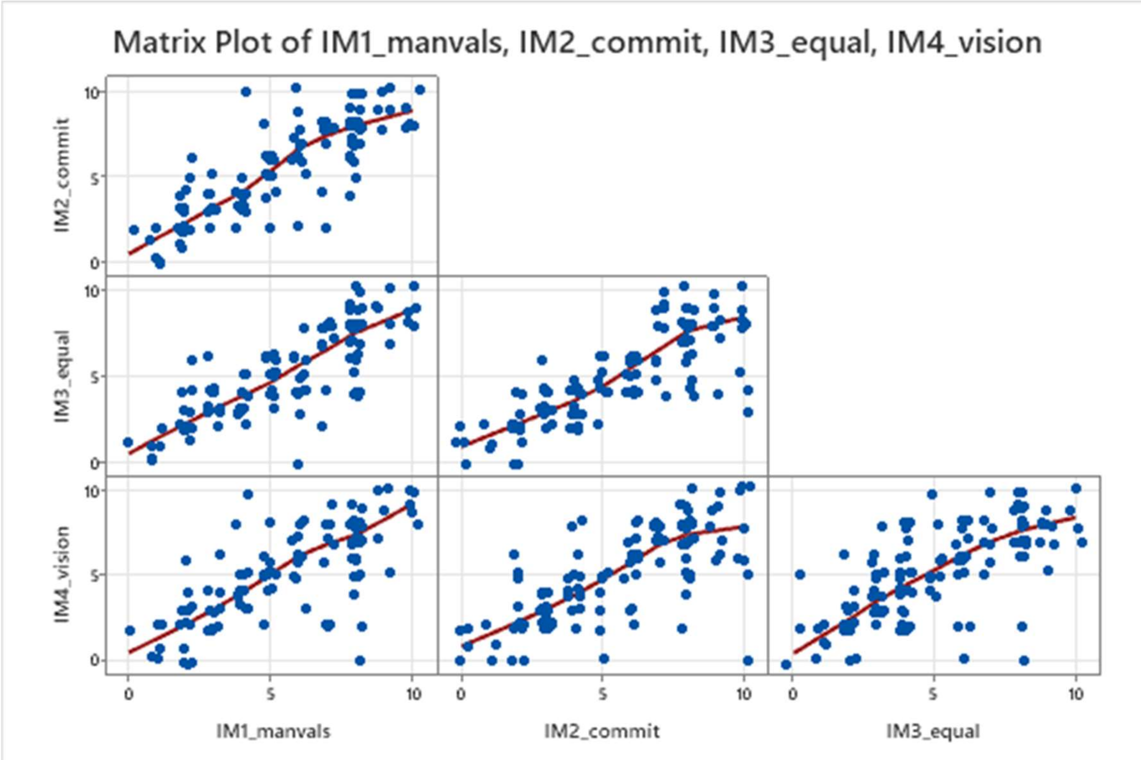
Variable	Total Count	Mean	StDev
IM1_manvals	123	5.504	2.616
IM2_commit	123	5.602	2.721
IM3_equal	123	5.081	2.588
IM4_vision	123	5.154	2.686
Total	123	21.341	9.668

Cronbach's Alpha

Alpha
0.9317

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
IM1_manvals	15.837	7.287	0.8794	0.7771	0.8979
IM2_commit	15.740	7.208	0.8698	0.7641	0.9007
IM3_equal	16.260	7.393	0.8394	0.7307	0.9110
IM4_vision	16.187	7.443	0.7719	0.6065	0.9329


Matrix Plot of IM1_manvals, IM2_commit, IM3_equal, IM4_vision
IM2_commit
IM3_equal
IM4_vision
IM1_manvals
IM2_commit
IM3_equal
0
5
10

Item Analysis of Cultural Hybridity (CH1, CH2, CH3)

Thematic Subset of Creolization

Correlation Matrix

	CH1_orgpract	CH2_collchng
CH2_collchng	0.868	
CH3_indvchng	0.788	0.828

Cell Contents
Pearson correlation

Covariance Matrix

	CH1_orgpract	CH2_collchng	CH3_indvchng
CH1_orgpract	7.3480		
CH2_collchng	6.3543	7.2939	
CH3_indvchng	5.9432	6.2200	7.7323

Item and Total Statistics

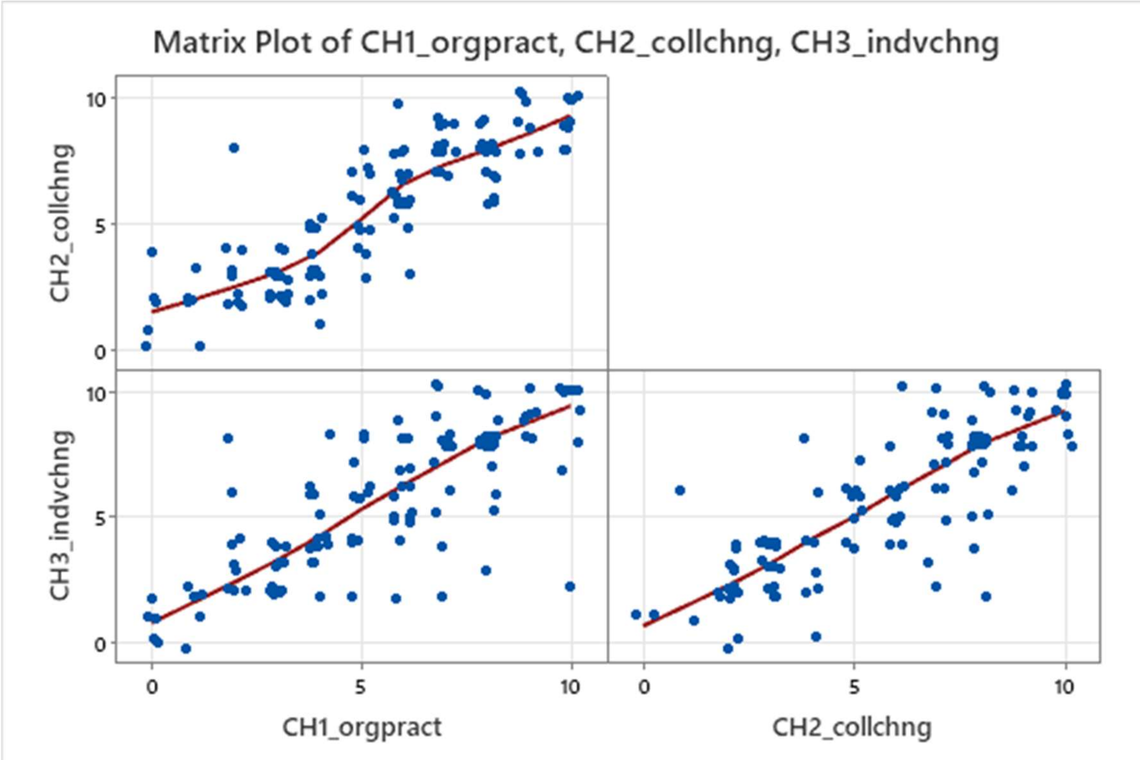
Variable	Total Count	Mean	StDev
CH1_orgpract	125	5.472	2.711
CH2_collchng	125	5.696	2.701
CH3_indvchng	125	5.560	2.781
Total	125	16.728	7.708

Cronbach's Alpha

Alpha
0.9351

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
CH1_orgpract	11.256	5.241	0.8656	0.7688	0.9058
CH2_collchng	11.032	5.193	0.8966	0.8081	0.8816
CH3_indvchng	11.168	5.230	0.8364	0.7056	0.9293


Matrix Plot of CH1_orgpract, CH2_collchng, CH3_indvchng
CH2_collchng
CH3_indvchng
CH1_orgpract
CH2_collchng
0
5
10

Item Analysis of Boundary Spanning (BS1, BS2, BS3, BS4) Thematic Subset of Creolization

* NOTE * 123 cases used, 2 cases contain missing values

Correlation Matrix

	BS1_mgrchat	BS2_collegchat	BS3_peerhelp
BS2_collegchat	0.657		
BS3_peerhelp	0.739	0.681	
BS4_mgmtexp	0.600	0.502	0.634

Cell Contents
Pearson correlation

Covariance Matrix

	BS1_mgrchat	BS2_collegchat	BS3_peerhelp	BS4_mgmtexp
BS1_mgrchat	8.9562			
BS2_collegchat	5.6084	8.1433		
BS3_peerhelp	6.8533	6.0179	9.6023	
BS4_mgmtexp	5.0283	4.0115	5.5021	7.8514

Item and Total Statistics

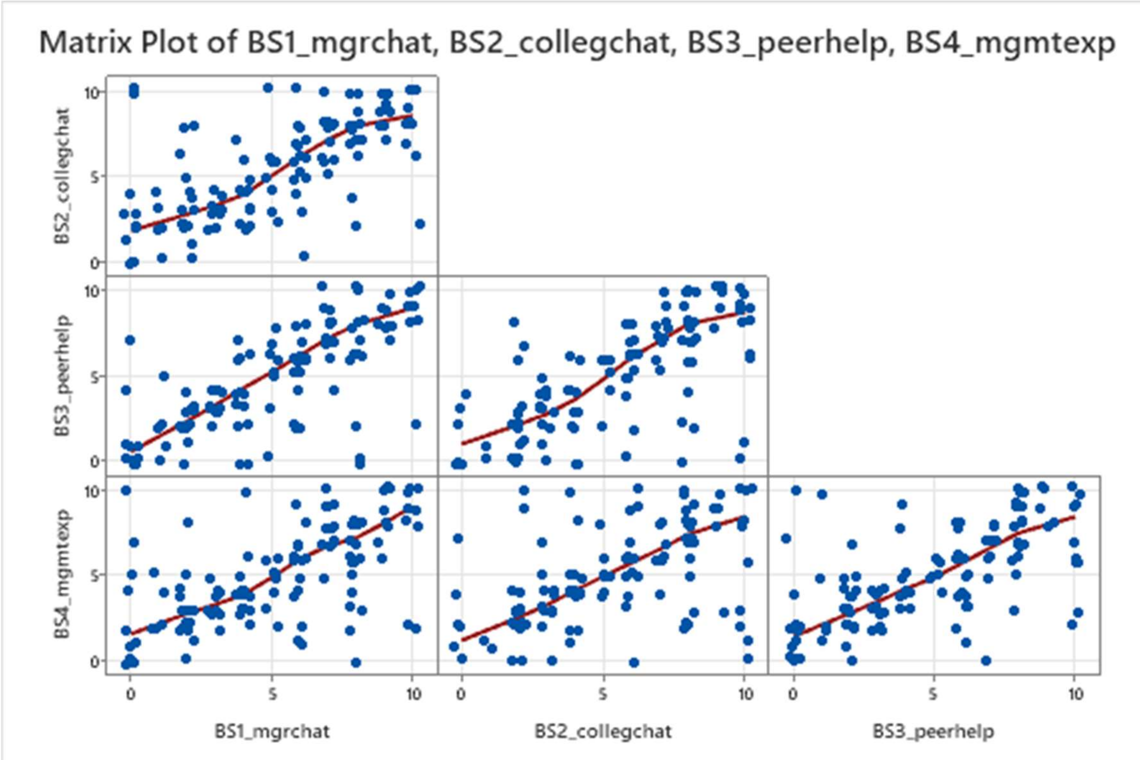
Variable	Total Count	Mean	StDev
BS1_mgrchat	123	5.138	2.993
BS2_collegchat	123	5.398	2.854
BS3_peerhelp	123	4.935	3.099
BS4_mgmtexp	123	5.033	2.802
Total	123	20.504	10.030

Cronbach's Alpha

Alpha
0.8754

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
BS1_mgrchat	15.366	7.527	0.7764	0.6112	0.8224
BS2_collegchat	15.106	7.822	0.7006	0.5165	0.8525
BS3_peerhelp	15.569	7.365	0.8050	0.6512	0.8101
BS4_mgmtexp	15.472	7.979	0.6504	0.4409	0.8708


Matrix Plot of BS1_mgrchat, BS2_collegchat, BS3_peerhelp, BS4_mgmtexp
BS2_collegchat
BS3_peerhelp
BS4_mgmtexp
BS1_mgrchat
BS2_collegchat
BS3_peerhelp
0
5
10

Item Analysis of Network Expansion (NE1, NE2, NE3) Thematic Subset of Creolization

* NOTE * 121 cases used, 4 cases contain missing values

Correlation Matrix

	NE1_srvision	NE2_exechelp
NE2_exechelp	0.469	
NE3_groupchng	0.626	0.748

Cell Contents
Pearson correlation

Covariance Matrix

	NE1_srvision	NE2_exechelp	NE3_groupchng
NE1_srvision	7.6022		
NE2_exechelp	3.5450	7.5216	
NE3_groupchng	4.8074	5.7152	7.7577

Item and Total Statistics

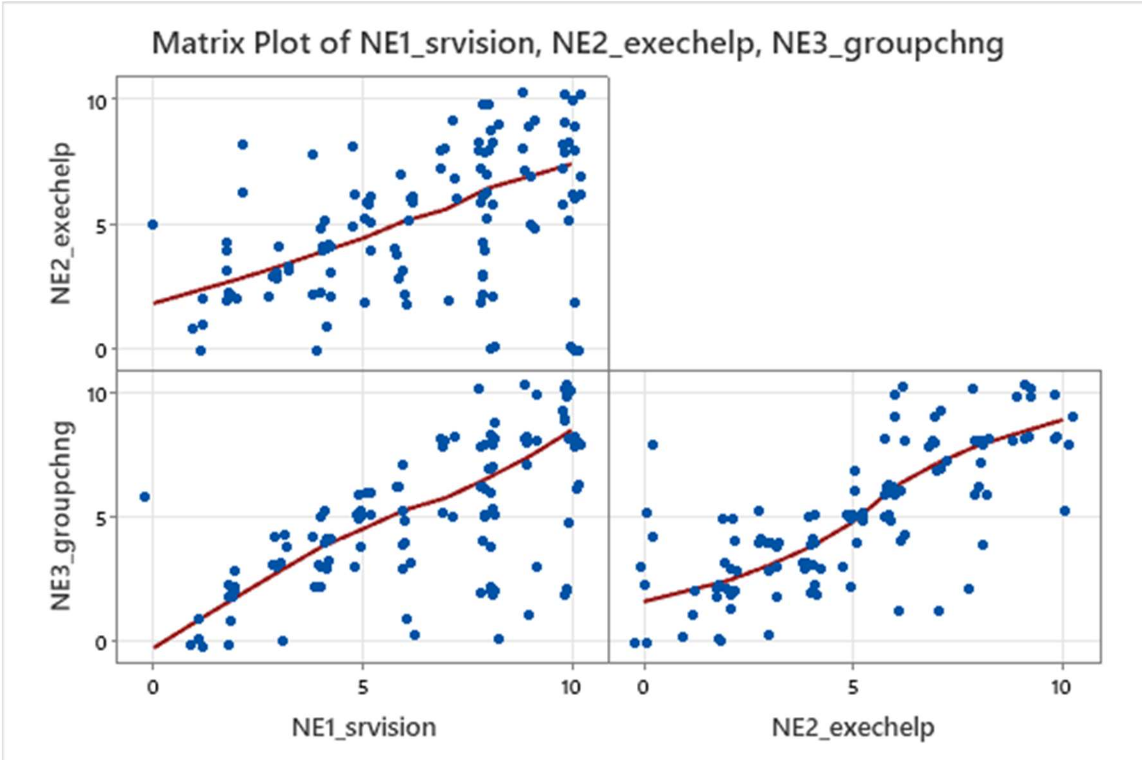
Variable	Total Count	Mean	StDev
NE1_srvision	121	6.372	2.757
NE2_exechelp	121	5.058	2.743
NE3_groupchng	121	5.025	2.785
Total	121	16.455	7.143

Cronbach's Alpha

Alpha
0.8272

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
NE1_srvision	10.083	5.168	0.5861	0.3919	0.8559
NE2_exechelp	11.397	4.997	0.6756	0.5598	0.7700
NE3_groupchng	11.430	4.713	0.8016	0.6569	0.6383


Matrix Plot of NE1_srvision, NE2_exechelp, NE3_groupchng
NE2_exechelp
NE3_groupchng
NE1_srvision
NE2_exechelp
0
5
10

Item Analysis of Loss Aversion (LA1, LA2)

Thematic Subset of Resistance to Change

* NOTE * 124 cases used, 1 cases contain missing values

* NOTE * Calculating omitted item statistics requires more than 2 variables.

Correlation Matrix

Pearson correlation of LA1_oldadv and LA2_oldeff = 0.725

Covariance Matrix

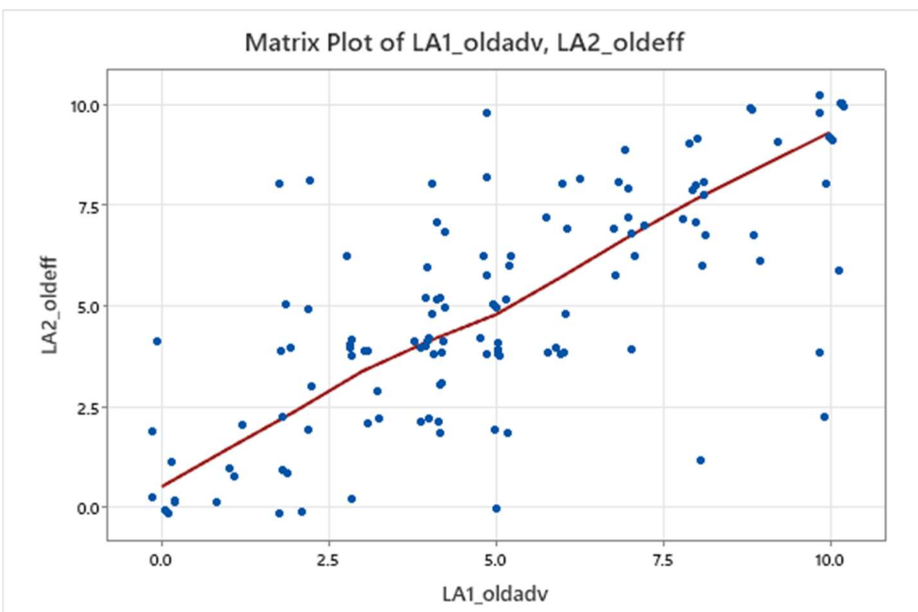
	LA1_oldadv	LA2_oldeff
LA1_oldadv	7.9347	
LA2_oldeff	5.8383	8.1675

Item and Total Statistics

Variable	Total Count	Mean	StDev
LA1_oldadv	124	5.0161	2.8169
LA2_oldeff	124	4.9435	2.8579
Total	124	9.9597	5.2706

Cronbach's Alpha

Alpha
0.8407



Item Analysis of Transactional Costs (TC1, TC2, TC3, TC4, TC5) Thematic Subset of Resistance to Change

* NOTE * 122 cases used, 3 cases contain missing values

Correlation Matrix

	TC1_switchtime	TC2_losework	TC3_hassle	TC4_effortworth
TC2_losework	0.675			
TC3_hassle	0.706	0.571		
TC4_effortworth	0.695	0.567	0.644	
TC5_noteasy	0.490	0.422	0.540	0.547

Cell Contents
Pearson correlation

Covariance Matrix

	TC1_switchtime	TC2_losework	TC3_hassle	TC4_effortworth
TC1_switchtime	7.2275			
TC2_losework	4.6280	6.4949		
TC3_hassle	5.3453	4.0975	7.9412	
TC4_effortworth	5.4269	4.1970	5.2706	8.4390
TC5_noteasy	3.2672	2.6687	3.7758	3.9468

	TC5_noteasy
TC5_noteasy	6.1593

Item and Total Statistics

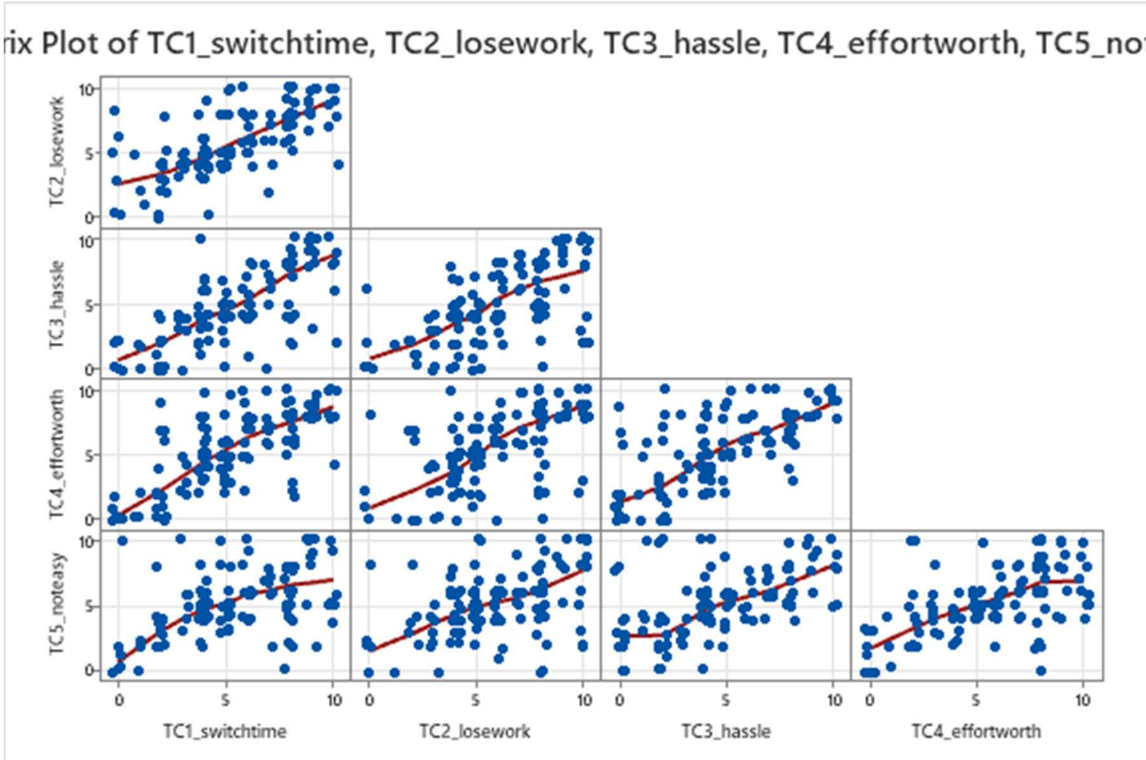
Variable	Total Count	Mean	StDev
TC1_switchtime	122	5.320	2.688
TC2_losework	122	5.795	2.548
TC3_hassle	122	4.672	2.818
TC4_effortworth	122	5.393	2.905
TC5_noteasy	122	5.197	2.482
Total	122	26.377	11.023

Cronbach's Alpha

Alpha
0.8770

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
TC1_switchtime	21.057	8.772	0.7916	0.6570	0.8302
TC2_losework	20.582	9.156	0.6682	0.4856	0.8599
TC3_hassle	21.705	8.752	0.7497	0.5752	0.8403
TC4_effortworth	20.984	8.683	0.7470	0.5679	0.8413
TC5_noteasy	21.180	9.383	0.5866	0.3636	0.8774


rix Plot of TC1_switchtime, TC2_losework, TC3_hassle, TC4_effortworth, TC5_not
TC2_losework
TC3_hassle
TC4_effortworth
TC5_noteasy
TC1_switchtime
TC2_losework
TC3_hassle
TC4_effortworth

Item Analysis of Social Norms (SN1, SN2, SN3)

Thematic Subset of Resistance to Change

* NOTE * 121 cases used, 4 cases contain missing values

Correlation Matrix

	SN1_colleagthink	SN2_mgrthink
SN2_mgrthink	0.575	
SN3_substhink	0.681	0.415

Cell Contents
Pearson correlation

Covariance Matrix

	SN1_colleagthink	SN2_mgrthink	SN3_substhink
SN1_colleagthink	7.3021		
SN2_mgrthink	3.7166	5.7164	
SN3_substhink	5.1885	2.7957	7.9504

Item and Total Statistics

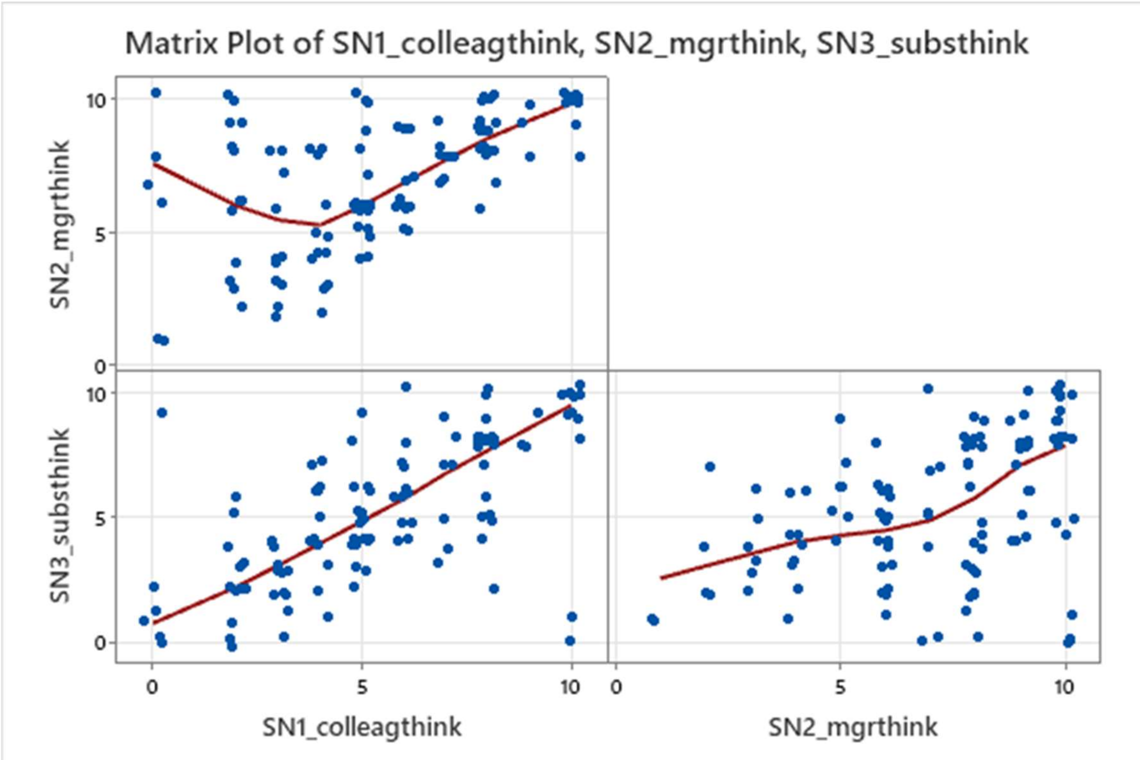
Variable	Total Count	Mean	StDev
SN1_colleagthink	121	5.496	2.702
SN2_mgrthink	121	6.983	2.391
SN3_substhink	121	5.240	2.820
Total	121	17.719	6.661

Cronbach's Alpha

Alpha
0.7911

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
SN1_colleagthink	12.223	4.388	0.7509	0.5673	0.5807
SN2_mgrthink	10.736	5.063	0.5380	0.3319	0.8098
SN3_substhink	12.479	4.522	0.6261	0.4645	0.7269


Matrix Plot of SN1_colleagthink, SN2_mgrthink, SN3_substhink
SN2_mgrthink
SN3_substhink
SN1_colleagthink
SN2_mgrthink
0
5
10

Item Analysis of Affective Inertia (AF1, AF2, AF3) Thematic Subset of Resistance to Change

* NOTE * 124 cases used, 1 cases contain missing values

Correlation Matrix

	AF1_stress	AF2_comfort
AF2_comfort	0.758	
AF3_enjoyold	0.782	0.845

Cell Contents
Pearson correlation

Covariance Matrix

	AF1_stress	AF2_comfort	AF3_enjoyold
AF1_stress	6.2077		
AF2_comfort	4.9701	6.9226	
AF3_enjoyold	5.2974	6.0477	7.4001

Item and Total Statistics

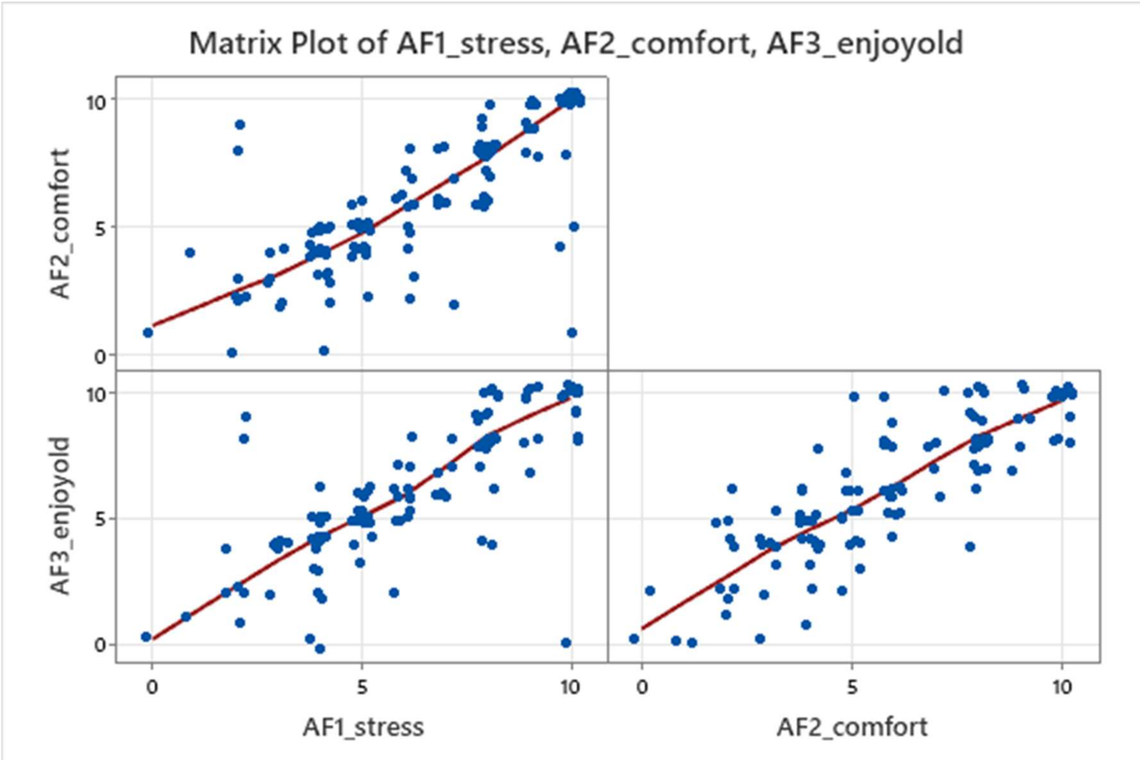
Variable	Total Count	Mean	StDev
AF1_stress	124	6.290	2.492
AF2_comfort	124	5.935	2.631
AF3_enjoyold	124	6.234	2.720
Total	124	18.460	7.291

Cronbach's Alpha

Alpha
0.9207

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
AF1_stress	12.169	5.140	0.8018	0.6443	0.9157
AF2_comfort	12.524	4.920	0.8512	0.7385	0.8755
AF3_enjoyold	12.226	4.803	0.8683	0.7607	0.8617


Matrix Plot of AF1_stress, AF2_comfort, AF3_enjoyold
AF2_comfort
AF3_enjoyold
AF1_stress
AF2_comfort
0
5
10

Item Analysis of Cognitive Inertia (CI1, CI2, CI3)

Thematic Subset of Resistance to Change

* NOTE * 121 cases used, 4 cases contain missing values

Correlation Matrix

	CI1_oldbest	CI2_oldeff
CI2_oldeff	0.830	
CI3_oldworks	0.839	0.838

Cell Contents
Pearson correlation

Covariance Matrix

	CI1_oldbest	CI2_oldeff	CI3_oldworks
CI1_oldbest	6.8517		
CI2_oldeff	5.5996	6.6376	
CI3_oldworks	5.7706	5.6761	6.9062

Item and Total Statistics

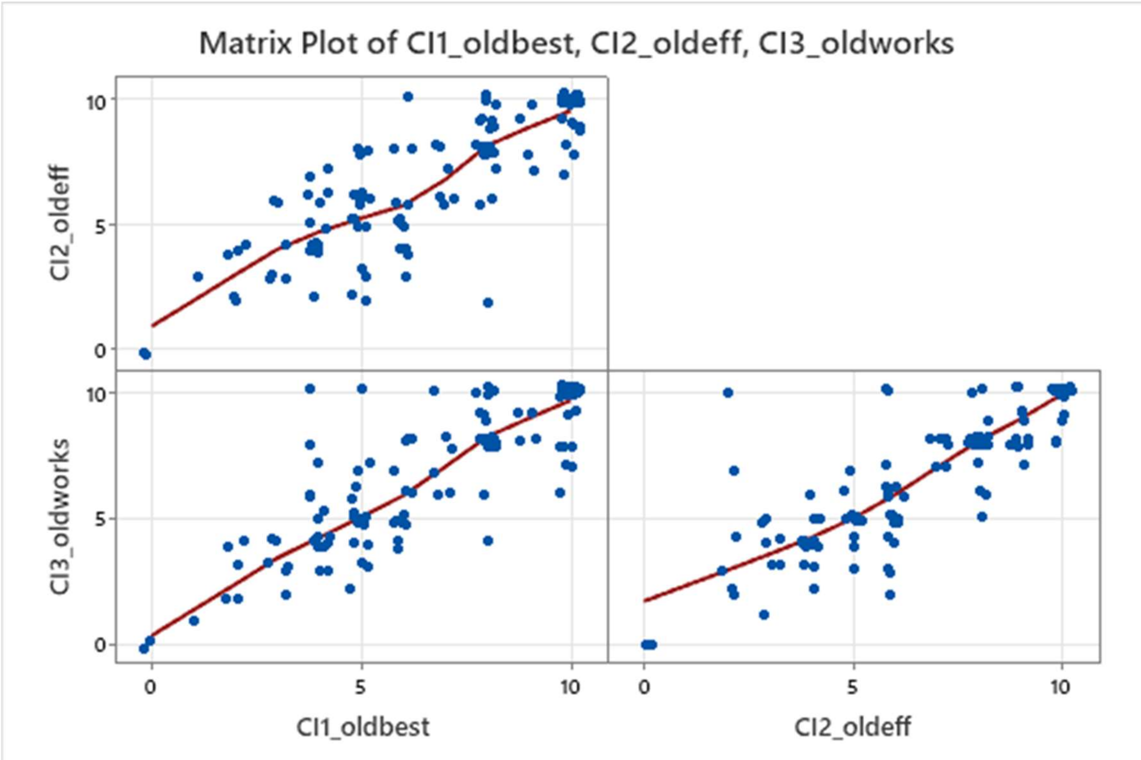
Variable	Total Count	Mean	StDev
CI1_oldbest	121	6.521	2.618
CI2_oldeff	121	6.620	2.576
CI3_oldworks	121	6.612	2.628
Total	121	19.752	7.382

Cronbach's Alpha

Alpha
0.9385

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
CI1_oldbest	13.231	4.990	0.8706	0.7581	0.9120
CI2_oldeff	13.132	5.030	0.8701	0.7573	0.9124
CI3_oldworks	13.140	4.969	0.8766	0.7685	0.9072



Matrix Plot of CI1_oldbest, CI2_oldeff, CI3_oldworks
CI2_oldeff
CI3_oldworks
CI1_oldbest
CI2_oldeff
0
5
10

Item Analysis of Resistive Intent (RI1, RI2, RI3, RI4)

Thematic Subset of Resistance to Change

* NOTE * 123 cases used, 2 cases contain missing values

Correlation Matrix

	RI1_support	RI2_cooper	RI3_intendcomply
RI2_cooper	0.818		
RI3_intendcomply	0.823	0.881	
RI4_notneed	0.788	0.638	0.614

Cell Contents
Pearson correlation

Covariance Matrix

	RI1_support	RI2_cooper	RI3_intendcomply	RI4_notneed
RI1_support	8.3830			
RI2_cooper	7.2493	9.3656		
RI3_intendcomply	6.9026	7.8052	8.3868	
RI4_notneed	7.0404	6.0273	5.4931	9.5331

Item and Total Statistics

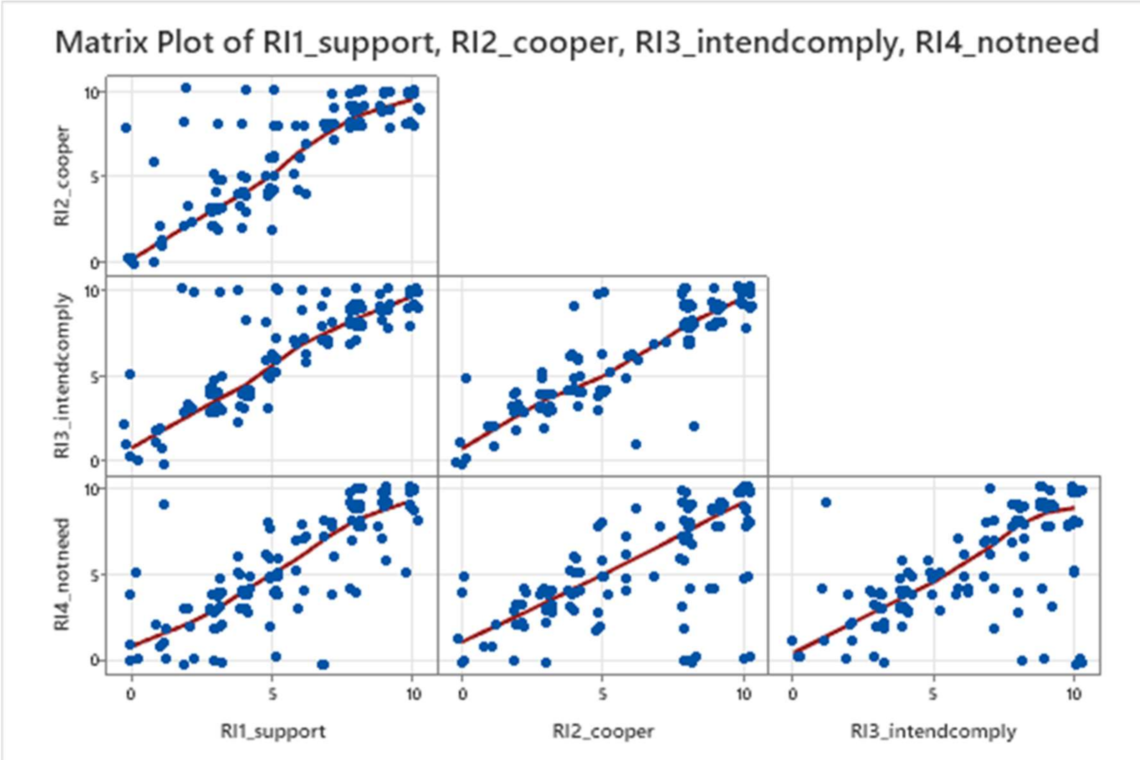
Variable	Total Count	Mean	StDev
RI1_support	123	5.512	2.895
RI2_cooper	123	6.057	3.060
RI3_intendcomply	123	6.252	2.896
RI4_notneed	123	5.382	3.088
Total	123	23.203	10.803

Cronbach's Alpha

Alpha
0.9258

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
RI1_support	17.691	8.120	0.9014	0.8169	0.8793
RI2_cooper	17.146	8.073	0.8533	0.8032	0.8946
RI3_intendcomply	16.951	8.241	0.8464	0.8099	0.8974
RI4_notneed	17.821	8.370	0.7182	0.6250	0.9404


Matrix Plot of RI1_support, RI2_cooper, RI3_intendcomply, RI4_notneed
RI2_cooper
RI3_intendcomply
RI4_notneed
RI1_support
RI2_cooper
RI3_intendcomply
0
5
10

WORKSHEET 1

Item Analysis of Creolization (IM1, IM2, IM3, IM4, CH1, CH2, CH3, BS1, BS2, BS3, BS4, NE1, NE2, NE3)

Thematic Subset of Fractal Emergence

* NOTE * 117 cases used, 8 cases contain missing values

Correlation Matrix

	IM1_manvals	IM2_commit	IM3_equal	IM4_vision
IM2_commit	0.842			
IM3_equal	0.815	0.816		
IM4_vision	0.743	0.735	0.676	
CH1_orgpract	0.736	0.659	0.670	0.691
CH2_collchng	0.734	0.676	0.677	0.708
CH3_indvchng	0.660	0.642	0.630	0.643
BS1_mgrchat	0.723	0.745	0.718	0.672
BS2_collegchat	0.594	0.585	0.576	0.535
BS3_peerhelp	0.627	0.571	0.641	0.669
BS4_mgmtexp	0.705	0.614	0.676	0.738
NE1_srvision	0.600	0.594	0.522	0.603
NE2_exechelp	0.707	0.656	0.736	0.700
NE3_groupchng	0.781	0.700	0.716	0.785

	CH1_orgpract	CH2_collchng	CH3_indvchng	BS1_mgrchat
CH2_collchng	0.870			
CH3_indvchng	0.790	0.817		
BS1_mgrchat	0.746	0.743	0.650	
BS2_collegchat	0.691	0.695	0.643	0.648
BS3_peerhelp	0.668	0.680	0.573	0.733
BS4_mgmtexp	0.621	0.610	0.567	0.589
NE1_srvision	0.526	0.599	0.547	0.444
NE2_exechelp	0.640	0.640	0.602	0.732
NE3_groupchng	0.685	0.692	0.669	0.666

	BS2_collegchat	BS3_peerhelp	BS4_mgmtexp	NE1_srvision
BS3_peerhelp	0.666			
BS4_mgmtexp	0.481	0.623		
NE1_srvision	0.510	0.430	0.554	
NE2_exechelp	0.602	0.716	0.709	0.456
NE3_groupchng	0.512	0.616	0.731	0.619

	NE2_exechelp
NE3_groupchng	0.745

Cell Contents
Pearson correlation

Covariance Matrix

	IM1_manvals	IM2_commit	IM3_equal	IM4_vision
IM1_manvals	6.7520			
IM2_commit	6.0183	7.5731		

IM3_equal	5.4817	5.8120	6.6995	
IM4_vision	5.2261	5.4724	4.7345	7.3210
CH1_orgpract	5.2263	4.9508	4.7331	5.1085
CH2_collchng	5.0893	4.9593	4.6758	5.1123
CH3_indvchng	4.7591	4.9051	4.5231	4.8252
BS1_mgrchat	5.6912	6.2109	5.6281	5.5044
BS2_collegchat	4.3992	4.5829	4.2447	4.1233
BS3_peerhelp	5.0645	4.8829	5.1544	5.6278
BS4_mgmtexp	5.1669	4.7725	4.9402	5.6382
NE1_srvision	4.2966	4.5109	3.7247	4.4978
NE2_exechelp	5.0723	4.9808	5.2606	5.2275
NE3_groupchng	5.7023	5.4160	5.2133	5.9695

	CH1_orgpract	**CH2_collchng**	**CH3_indvchng**	**BS1_mgrchat**
CH1_orgpract	7.4590			
CH2_collchng	6.3352	7.1146		
CH3_indvchng	5.9855	6.0492	7.7000	
BS1_mgrchat	6.1690	5.9999	5.4585	9.1695
BS2_collegchat	5.3727	5.2838	5.0849	5.5902
BS3_peerhelp	5.6681	5.6400	4.9428	6.9033
BS4_mgmtexp	4.7892	4.5917	4.4400	5.0315
NE1_srvision	3.9586	4.4052	4.1888	3.7084
NE2_exechelp	4.8236	4.7168	4.6147	6.1214
NE3_groupchng	5.2630	5.1872	5.2164	5.6669

	BS2_collegchat	**BS3_peerhelp**	**BS4_mgmtexp**	**NE1_srvision**
BS2_collegchat	8.1127			
BS3_peerhelp	5.9012	9.6637		
BS4_mgmtexp	3.8700	5.4647	7.9652	
NE1_srvision	4.0066	3.6863	4.3075	7.6027
NE2_exechelp	4.7314	6.1459	5.5272	3.4695
NE3_groupchng	4.1001	5.3877	5.7993	4.8002

	NE2_exechelp	**NE3_groupchng**
NE2_exechelp	7.6233	
NE3_groupchng	5.7825	7.9045

Item and Total Statistics

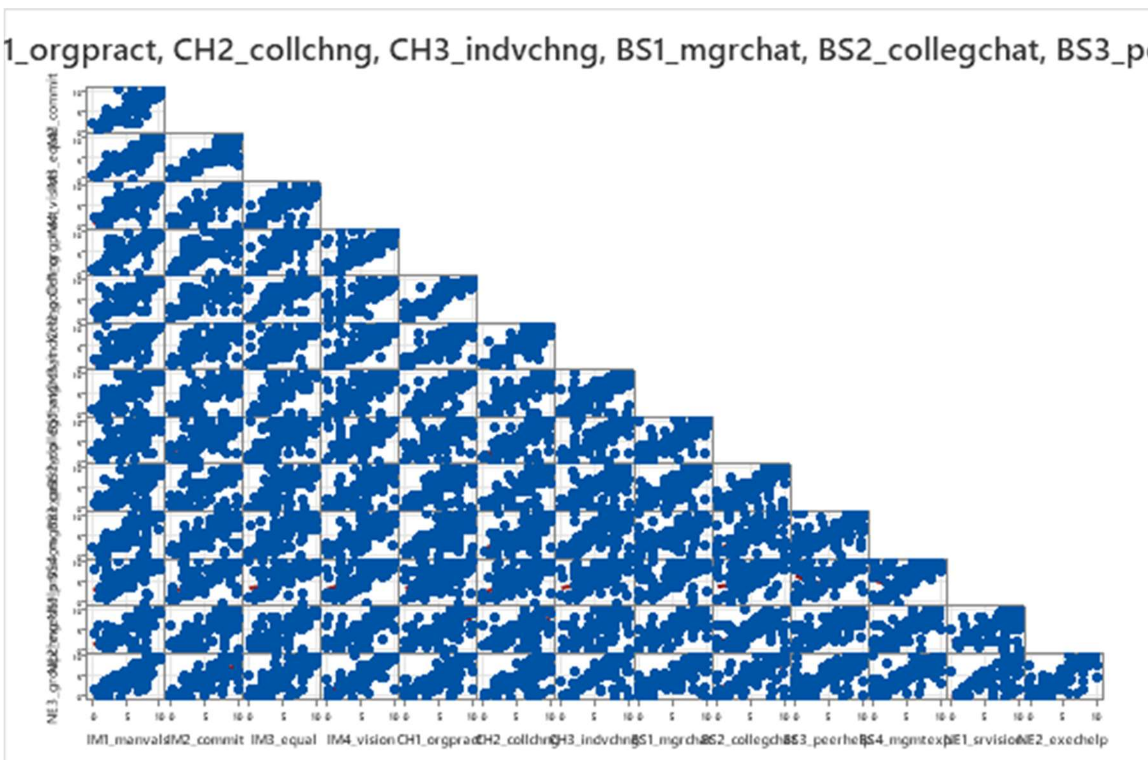
Variable	Total Count	Mean	StDev
IM1_manvals	117	5.513	2.598
IM2_commit	117	5.581	2.752
IM3_equal	117	5.085	2.588
IM4_vision	117	5.179	2.706
CH1_orgpract	117	5.496	2.731
CH2_collchng	117	5.761	2.667
CH3_indvchng	117	5.632	2.775
BS1_mgrchat	117	5.214	3.028
BS2_collegchat	117	5.462	2.848
BS3_peerhelp	117	5.009	3.109
BS4_mgmtexp	117	5.094	2.822
NE1_srvision	117	6.393	2.757
NE2_exechelp	117	5.077	2.761
NE3_groupchng	117	5.026	2.811
Total	117	75.521	32.176

Cronbach's Alpha

Alpha
0.9639

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
IM1_manvals	70.01	29.90	0.8648	0.8206	0.9599
IM2_commit	69.94	29.88	0.8206	0.8198	0.9607
IM3_equal	70.44	30.01	0.8257	0.7716	0.9606
IM4_vision	70.34	29.90	0.8291	0.7553	0.9605
CH1_orgpract	70.03	29.85	0.8388	0.8121	0.9603
CH2_collchng	69.76	29.87	0.8541	0.8345	0.9600
CH3_indvchng	69.89	29.96	0.7818	0.7206	0.9615
BS1_mgrchat	70.31	29.64	0.8209	0.7599	0.9607
BS2_collegchat	70.06	30.08	0.7155	0.6264	0.9629
BS3_peerhelp	70.51	29.74	0.7622	0.6896	0.9621
BS4_mgmtexp	70.43	29.98	0.7605	0.6716	0.9619
NE1_srvision	69.13	30.34	0.6402	0.5358	0.9644
NE2_exechelp	70.44	29.91	0.8049	0.7369	0.9610
NE3_groupchng	70.50	29.81	0.8294	0.7662	0.9605



Item Analysis of Resistance To Change (LA1, LA2, TC1, TC2, TC3, TC4, TC5, SN1, SN2, SN3, AF1, AF2, AF3, CI1, CI2, CI3, RI1, RI2, RI3, RI4)

Thematic Subset of Fractal Emergence

* NOTE * 111 cases used, 14 cases contain missing values

Correlation Matrix

	LA1_oldadv	LA2_oldeff	TC1_switchtime	TC2_losework
LA2_oldeff	0.757			
TC1_switchtime	0.659	0.736		
TC2_losework	0.595	0.641	0.678	
TC3_hassle	0.670	0.675	0.707	0.607
TC4_effortworth	0.632	0.704	0.716	0.578
TC5_noteasy	0.416	0.527	0.498	0.450
SN1_colleagthink	0.562	0.617	0.599	0.582
SN2_mgrthink	0.206	0.276	0.317	0.375
SN3_substhink	0.565	0.625	0.629	0.469
AF1_stress	0.388	0.456	0.545	0.535
AF2_comfort	0.457	0.521	0.619	0.536
AF3_enjoyold	0.570	0.624	0.670	0.662
CI1_oldbest	0.414	0.443	0.505	0.629
CI2_oldeff	0.442	0.490	0.610	0.585
CI3_oldworks	0.493	0.513	0.604	0.579
RI1_support	0.663	0.729	0.678	0.631
RI2_cooper	0.519	0.566	0.609	0.618
RI3_intendcomply	0.474	0.528	0.533	0.491
RI4_notneed	0.603	0.697	0.751	0.663

	TC3_hassle	TC4_effortworth	TC5_noteasy	SN1_colleagthink
TC4_effortworth	0.660			
TC5_noteasy	0.527	0.559		
SN1_colleagthink	0.486	0.608	0.290	
SN2_mgrthink	0.130	0.387	0.193	0.606
SN3_substhink	0.527	0.696	0.283	0.674
AF1_stress	0.373	0.663	0.406	0.600
AF2_comfort	0.410	0.676	0.493	0.617
AF3_enjoyold	0.487	0.739	0.525	0.664
CI1_oldbest	0.369	0.620	0.458	0.607
CI2_oldeff	0.426	0.694	0.471	0.614
CI3_oldworks	0.424	0.648	0.463	0.624
RI1_support	0.518	0.742	0.407	0.771
RI2_cooper	0.431	0.648	0.407	0.737
RI3_intendcomply	0.326	0.640	0.427	0.717
RI4_notneed	0.597	0.743	0.363	0.648

	SN2_mgrthink	SN3_substhink	AF1_stress	AF2_comfort
SN3_substhink	0.416			

AF1_stress	0.482	0.577		
AF2_comfort	0.455	0.609	0.767	
AF3_enjoyold	0.475	0.618	0.788	0.842
CI1_oldbest	0.628	0.586	0.765	0.733
CI2_oldeff	0.616	0.635	0.772	0.778
CI3_oldworks	0.574	0.618	0.745	0.746
RI1_support	0.524	0.708	0.673	0.669
RI2_cooper	0.577	0.625	0.737	0.744
RI3_intendcomply	0.570	0.533	0.705	0.690
RI4_notneed	0.420	0.637	0.566	0.641

	AF3_enjoyold	CI1_oldbest	CI2_oldeff	CI3_oldworks
CI1_oldbest	0.797			
CI2_oldeff	0.818	0.822		
CI3_oldworks	0.823	0.829	0.827	
RI1_support	0.778	0.648	0.727	0.718
RI2_cooper	0.823	0.733	0.758	0.769
RI3_intendcomply	0.758	0.686	0.734	0.746
RI4_notneed	0.680	0.581	0.608	0.593

	RI1_support	RI2_cooper	RI3_intendcomply
RI2_cooper	0.831		
RI3_intendcomply	0.832	0.874	
RI4_notneed	0.784	0.650	0.616

Cell Contents
Pearson correlation

Covariance Matrix

	LA1_oldadv	LA2_oldeff	TC1_switchtime	TC2_losework
LA1_oldadv	8.1633			
LA2_oldeff	6.0921	7.9324		
TC1_switchtime	5.0525	5.5663	7.2031	
TC2_losework	4.4053	4.6768	4.7174	6.7112
TC3_hassle	5.4407	5.4075	5.3930	4.4726
TC4_effortworth	5.2360	5.7514	5.5770	4.3453
TC5_noteasy	2.8853	3.6061	3.2442	2.8305
SN1_colleagthink	4.3741	4.7269	4.3746	4.1024
SN2_mgrthink	1.4360	1.9011	2.0798	2.3781
SN3_substhink	4.5418	4.9447	4.7474	3.4167
AF1_stress	2.7522	3.1856	3.6283	3.4409
AF2_comfort	3.4534	3.8858	4.3974	3.6777
AF3_enjoyold	4.3679	4.7124	4.8175	4.5944
CI1_oldbest	3.1009	3.2741	3.5579	4.2785
CI2_oldeff	3.2485	3.5485	4.2121	3.9030
CI3_oldworks	3.7121	3.8030	4.2667	3.9485
RI1_support	5.5835	6.0531	5.3585	4.8152
RI2_cooper	4.5388	4.8823	5.0017	4.9010
RI3_intendcomply	3.9424	4.3242	4.1606	3.6970
RI4_notneed	5.3361	6.0781	6.2462	5.3199

	TC3_hassle	TC4_effortworth	TC5_noteasy	SN1_colleagthink
TC3_hassle	8.0857			
TC4_effortworth	5.4441	8.4154		
TC5_noteasy	3.6408	3.9361	5.9002	

SN1_colleagthink	3.7611	4.8040	1.9172	7.4100
SN2_mgrthink	0.9043	2.7450	1.1489	4.0378
SN3_substhink	4.2147	5.6749	1.9342	5.1543
AF1_stress	2.6337	4.7766	2.4477	4.0578
AF2_comfort	3.0834	5.1940	3.1666	4.4458
AF3_enjoyold	3.7072	5.7417	3.4189	4.8455
CI1_oldbest	2.7540	4.7170	2.9224	4.3348
CI2_oldeff	3.1212	5.1788	2.9455	4.3030
CI3_oldworks	3.1758	4.9515	2.9636	4.4758
RI1_support	4.3386	6.3408	2.9138	6.1813
RI2_cooper	3.7538	5.7531	3.0287	6.1396
RI3_intendcomply	2.6970	5.4030	3.0182	5.6788
RI4_notneed	5.2555	6.6747	2.7344	5.4624

	SN2_mgrthink	SN3_substhink	AF1_stress	AF2_comfort
SN2_mgrthink	5.9815			
SN3_substhink	2.8600	7.9017		
AF1_stress	2.9249	4.0256	6.1623	
AF2_comfort	2.9443	4.5280	5.0417	7.0051
AF3_enjoyold	3.1133	4.6570	5.2400	5.9695
CI1_oldbest	4.0282	4.3260	4.9861	5.0895
CI2_oldeff	3.8758	4.5909	4.9333	5.2970
CI3_oldworks	3.6939	4.5727	4.8697	5.1970
RI1_support	3.7744	5.8671	4.9238	5.2197
RI2_cooper	4.3206	5.3776	5.6042	6.0268
RI3_intendcomply	4.0515	4.3545	5.0939	5.3121
RI4_notneed	3.1816	5.5450	4.3550	5.2582

	AF3_enjoyold	CI1_oldbest	CI2_oldeff	CI3_oldworks
AF3_enjoyold	7.1810			
CI1_oldbest	5.6065	6.8862		
CI2_oldeff	5.6424	5.5485	6.6242	
CI3_oldworks	5.8061	5.7303	5.6061	6.9333
RI1_support	6.1413	5.0066	5.5091	5.5727
RI2_cooper	6.7499	5.8887	5.9727	6.2000
RI3_intendcomply	5.9121	5.2333	5.4939	5.7121
RI4_notneed	5.6486	4.7211	4.8455	4.8364

	RI1_support	RI2_cooper	RI3_intendcomply	RI4_notneed
RI1_support	8.6796			
RI2_cooper	7.4916	9.3725		
RI3_intendcomply	7.1273	7.7818	8.4606	
RI4_notneed	7.1536	6.1609	5.5545	9.5975

Item and Total Statistics

Variable	Total Count	Mean	StDev
LA1_oldadv	111	4.98	2.86
LA2_oldeff	111	5.06	2.82
TC1_switchtime	111	5.39	2.68
TC2_losework	111	5.79	2.59
TC3_hassle	111	4.74	2.84
TC4_effortworth	111	5.48	2.90
TC5_noteasy	111	5.19	2.43
SN1_colleagthink	111	5.58	2.72
SN2_mgrthink	111	6.98	2.45

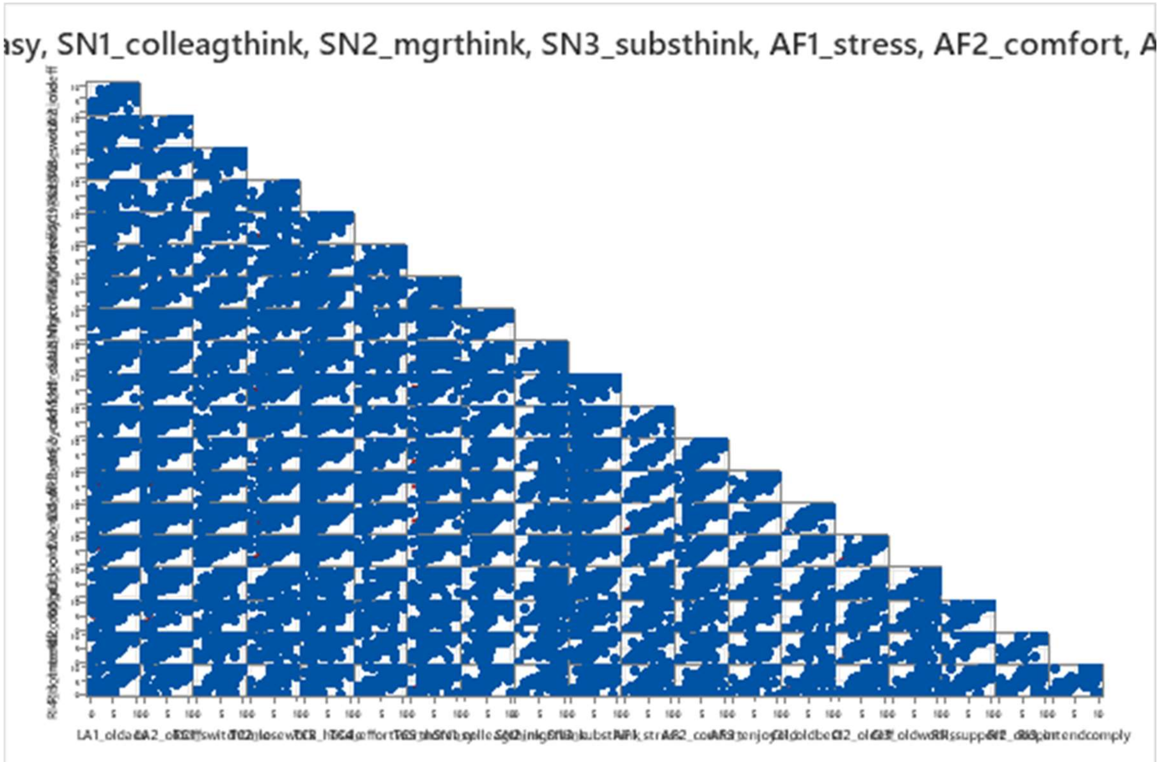
SN3_substhink	111	5.30	2.81
AF1_stress	111	6.37	2.48
AF2_comfort	111	5.94	2.65
AF3_enjoyold	111	6.23	2.68
CI1_oldbest	111	6.55	2.62
CI2_oldeff	111	6.67	2.57
CI3_oldworks	111	6.67	2.63
RI1_support	111	5.59	2.95
RI2_cooper	111	6.14	3.06
RI3_intendcomply	111	6.33	2.91
RI4_notneed	111	5.49	3.10
Total	111	116.46	43.19

Cronbach's Alpha

Alpha
0.9677

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
LA1_oldadv	111.48	41.21	0.6752	0.6724	0.9670
LA2_oldeff	111.40	41.05	0.7476	0.7689	0.9662
TC1_switchtime	111.07	41.06	0.7841	0.7547	0.9658
TC2_losework	110.67	41.27	0.7289	0.6983	0.9664
TC3_hassle	111.72	41.36	0.6223	0.7063	0.9676
TC4_effortworth	110.98	40.75	0.8311	0.7806	0.9652
TC5_noteasy	111.27	41.84	0.5383	0.5647	0.9683
SN1_colleagthink	110.88	41.03	0.7805	0.7504	0.9658
SN2_mgrthink	109.48	41.82	0.5417	0.6106	0.9683
SN3_substhink	111.16	41.07	0.7391	0.7150	0.9663
AF1_stress	110.09	41.25	0.7707	0.7359	0.9659
AF2_comfort	110.52	41.04	0.8027	0.7860	0.9656
AF3_enjoyold	110.23	40.80	0.8843	0.8704	0.9646
CI1_oldbest	109.91	41.09	0.7893	0.8327	0.9657
CI2_oldeff	109.79	41.03	0.8312	0.8289	0.9653
CI3_oldworks	109.79	40.99	0.8254	0.8048	0.9653
RI1_support	110.86	40.57	0.8815	0.8835	0.9645
RI2_cooper	110.32	40.56	0.8502	0.8629	0.9649
RI3_intendcomply	110.13	40.84	0.7959	0.8672	0.9656
RI4_notneed	110.97	40.68	0.7963	0.7727	0.9656


asy, SN1_colleagthink, SN2_mgrthink, SN3_substhink, AF1_stress, AF2_comfort, A

WORKSHEET 1

Item Analysis of Overall Fractal Emergence (Creolization and Resistance to Change)

* NOTE * 104 cases used, 21 cases contain missing values

Correlation Matrix

	IM1_manvals	IM2_commit	IM3_equal	IM4_vision
IM2_commit	0.833			
IM3_equal	0.804	0.810		
IM4_vision	0.737	0.737	0.680	
CH1_orgpract	0.727	0.645	0.661	0.684
CH2_collchng	0.719	0.654	0.660	0.707
CH3_indvchng	0.625	0.612	0.597	0.625
BS1_mgrchat	0.698	0.725	0.693	0.667
BS2_collegchat	0.600	0.595	0.580	0.517
BS3_peerhelp	0.605	0.556	0.628	0.653
BS4_mgmtexp	0.686	0.588	0.655	0.735
NE1_srvision	0.604	0.587	0.512	0.610
NE2_exechelp	0.684	0.641	0.730	0.681
NE3_groupchng	0.775	0.693	0.705	0.776
LA1_oldadv	0.444	0.470	0.507	0.639
LA2_oldeff	0.500	0.570	0.587	0.705
TC1_switchtime	0.448	0.611	0.569	0.617
TC2_losework	0.557	0.573	0.469	0.621
TC3_hassle	0.470	0.570	0.638	0.567
TC4_effortworth	0.551	0.630	0.610	0.695
TC5_noteasy	0.290	0.361	0.418	0.346
SN1_colleagthink	0.671	0.633	0.594	0.742
SN2_mgrthink	0.458	0.388	0.363	0.463
SN3_substhink	0.557	0.633	0.594	0.698
AF1_stress	0.565	0.541	0.400	0.546
AF2_comfort	0.535	0.585	0.462	0.561
AF3_enjoyold	0.673	0.651	0.517	0.670
CI1_oldbest	0.628	0.593	0.458	0.570
CI2_oldeff	0.624	0.602	0.498	0.621
CI3_oldworks	0.594	0.594	0.485	0.576
RI1_support	0.693	0.693	0.593	0.790
RI2_cooper	0.771	0.766	0.637	0.695
RI3_intendcomply	0.643	0.632	0.487	0.625
RI4_notneed	0.548	0.645	0.556	0.701

	CH1_orgpract	CH2_collchng	CH3_indvchng	BS1_mgrchat
CH2_collchng	0.863			
CH3_indvchng	0.772	0.799		
BS1_mgrchat	0.746	0.734	0.624	
BS2_collegchat	0.723	0.715	0.651	0.665
BS3_peerhelp	0.650	0.670	0.545	0.723
BS4_mgmtexp	0.594	0.582	0.519	0.564
NE1_srvision	0.550	0.626	0.552	0.431
NE2_exechelp	0.614	0.613	0.563	0.724

NE3_groupchng	0.667	0.676	0.642	0.653
LA1_oldadv	0.376	0.458	0.368	0.525
LA2_oldeff	0.485	0.520	0.438	0.593
TC1_switchtime	0.511	0.550	0.516	0.668
TC2_losework	0.431	0.457	0.413	0.550
TC3_hassle	0.410	0.430	0.367	0.530
TC4_effortworth	0.598	0.662	0.666	0.604
TC5_noteasy	0.248	0.305	0.354	0.219
SN1_colleagthink	0.679	0.721	0.672	0.702
SN2_mgrthink	0.577	0.639	0.610	0.423
SN3_substhink	0.630	0.649	0.590	0.678
AF1_stress	0.595	0.629	0.633	0.526
AF2_comfort	0.599	0.675	0.670	0.547
AF3_enjoyold	0.580	0.676	0.630	0.595
CI1_oldbest	0.624	0.679	0.618	0.563
CI2_oldeff	0.655	0.735	0.677	0.577
CI3_oldworks	0.592	0.664	0.570	0.566
RI1_support	0.674	0.688	0.667	0.681
RI2_cooper	0.665	0.737	0.655	0.714
RI3_intendcomply	0.614	0.713	0.639	0.584
RI4_notneed	0.620	0.606	0.617	0.689

	BS2_collegchat	**BS3_peerhelp**	**BS4_mgmtexp**	**NE1_srvision**
BS3_peerhelp	0.679			
BS4_mgmtexp	0.469	0.602		
NE1_srvision	0.514	0.437	0.550	
NE2_exechelp	0.588	0.702	0.694	0.469
NE3_groupchng	0.487	0.594	0.712	0.633
LA1_oldadv	0.394	0.539	0.537	0.310
LA2_oldeff	0.366	0.536	0.596	0.403
TC1_switchtime	0.474	0.574	0.541	0.394
TC2_losework	0.427	0.507	0.564	0.459
TC3_hassle	0.446	0.458	0.514	0.292
TC4_effortworth	0.522	0.549	0.497	0.512
TC5_noteasy	0.360	0.267	0.239	0.276
SN1_colleagthink	0.471	0.603	0.628	0.581
SN2_mgrthink	0.487	0.417	0.371	0.657
SN3_substhink	0.528	0.541	0.591	0.514
AF1_stress	0.550	0.367	0.402	0.544
AF2_comfort	0.530	0.430	0.470	0.547
AF3_enjoyold	0.542	0.513	0.528	0.620
CI1_oldbest	0.595	0.425	0.459	0.601
CI2_oldeff	0.602	0.472	0.472	0.604
CI3_oldworks	0.561	0.431	0.450	0.578
RI1_support	0.524	0.621	0.610	0.606
RI2_cooper	0.597	0.541	0.574	0.655
RI3_intendcomply	0.482	0.446	0.429	0.617
RI4_notneed	0.512	0.622	0.592	0.574

	NE2_exechelp	**NE3_groupchng**	**LA1_oldadv**	**LA2_oldeff**
NE3_groupchng	0.725			
LA1_oldadv	0.569	0.492		
LA2_oldeff	0.571	0.555	0.773	
TC1_switchtime	0.666	0.541	0.659	0.737
TC2_losework	0.484	0.541	0.598	0.634

TC3_hassle	0.570	0.494	0.674	0.677
TC4_effortworth	0.591	0.603	0.645	0.699
TC5_noteasy	0.259	0.255	0.416	0.527
SN1_colleagthink	0.660	0.727	0.565	0.616
SN2_mgrthink	0.381	0.424	0.194	0.261
SN3_substhink	0.541	0.610	0.580	0.623
AF1_stress	0.403	0.463	0.389	0.444
AF2_comfort	0.452	0.528	0.477	0.515
AF3_enjoyold	0.556	0.619	0.579	0.626
CI1_oldbest	0.417	0.511	0.409	0.436
CI2_oldeff	0.471	0.530	0.431	0.484
CI3_oldworks	0.503	0.521	0.494	0.510
RI1_support	0.649	0.694	0.671	0.728
RI2_cooper	0.623	0.684	0.520	0.559
RI3_intendcomply	0.480	0.600	0.472	0.523
RI4_notneed	0.624	0.688	0.615	0.690

	TC1_switchtime	**TC2_losework**	**TC3_hassle**	**TC4_effortworth**
TC2_losework	0.671			
TC3_hassle	0.712	0.610		
TC4_effortworth	0.715	0.565	0.659	
TC5_noteasy	0.494	0.445	0.533	0.559
SN1_colleagthink	0.591	0.567	0.498	0.605
SN2_mgrthink	0.297	0.343	0.127	0.369
SN3_substhink	0.631	0.464	0.531	0.691
AF1_stress	0.537	0.518	0.363	0.649
AF2_comfort	0.626	0.535	0.410	0.669
AF3_enjoyold	0.669	0.663	0.491	0.737
CI1_oldbest	0.497	0.619	0.365	0.612
CI2_oldeff	0.601	0.571	0.420	0.689
CI3_oldworks	0.597	0.567	0.426	0.641
RI1_support	0.671	0.617	0.520	0.735
RI2_cooper	0.598	0.597	0.428	0.635
RI3_intendcomply	0.522	0.469	0.327	0.635
RI4_notneed	0.750	0.655	0.601	0.736

	TC5_noteasy	**SN1_colleagthink**	**SN2_mgrthink**	**SN3_substhink**
SN1_colleagthink	0.282			
SN2_mgrthink	0.180	0.585		
SN3_substhink	0.279	0.676	0.403	
AF1_stress	0.402	0.591	0.458	0.564
AF2_comfort	0.494	0.622	0.448	0.599
AF3_enjoyold	0.523	0.662	0.462	0.609
CI1_oldbest	0.457	0.596	0.609	0.576
CI2_oldeff	0.468	0.603	0.602	0.631
CI3_oldworks	0.463	0.611	0.550	0.610
RI1_support	0.401	0.764	0.501	0.705
RI2_cooper	0.401	0.728	0.553	0.622
RI3_intendcomply	0.421	0.705	0.546	0.528
RI4_notneed	0.359	0.641	0.401	0.631

	AF1_stress	**AF2_comfort**	**AF3_enjoyold**	**CI1_oldbest**
AF2_comfort	0.763			
AF3_enjoyold	0.785	0.844		
CI1_oldbest	0.757	0.737	0.796	
CI2_oldeff	0.766	0.787	0.819	0.817

CI3_oldworks	0.735	0.749	0.822	0.823
RI1_support	0.660	0.666	0.775	0.635
RI2_cooper	0.726	0.748	0.826	0.724
RI3_intendcomply	0.699	0.695	0.758	0.675
RI4_notneed	0.552	0.635	0.678	0.572

	CI2_oldeff	CI3_oldworks	RI1_support	RI2_cooper
CI3_oldworks	0.822			
RI1_support	0.718	0.708		
RI2_cooper	0.750	0.761	0.823	
RI3_intendcomply	0.726	0.738	0.826	0.870
RI4_notneed	0.601	0.583	0.779	0.639

	RI3_intendcomply
RI4_notneed	0.608

Cell Contents
Pearson correlation

Covariance Matrix

	IM1_manvals	IM2_commit	IM3_equal	IM4_vision
IM1_manvals	6.730			
IM2_commit	5.877	7.399		
IM3_equal	5.407	5.712	6.724	
IM4_vision	5.246	5.496	4.836	7.524
CH1_orgpract	5.087	4.730	4.624	5.059
CH2_collchng	4.913	4.686	4.509	5.106
CH3_indvchng	4.460	4.580	4.255	4.716
BS1_mgrchat	5.543	6.037	5.497	5.594
BS2_collegchat	4.514	4.691	4.362	4.107
BS3_peerhelp	4.979	4.794	5.163	5.685
BS4_mgmtexp	5.046	4.535	4.819	5.715
NE1_srvision	4.363	4.450	3.701	4.659
NE2_exechelp	4.911	4.825	5.241	5.169
NE3_groupchng	5.731	5.378	5.214	6.069
LA1_oldadv	3.346	3.713	3.821	5.097
LA2_oldeff	3.729	4.455	4.373	5.561
TC1_switchtime	3.182	4.551	4.039	4.638
TC2_losework	3.764	4.055	3.168	4.435
TC3_hassle	3.523	4.477	4.778	4.490
TC4_effortworth	4.189	5.029	4.641	5.587
TC5_noteasy	1.880	2.453	2.705	2.368
SN1_colleagthink	4.789	4.739	4.237	5.603
SN2_mgrthink	2.882	2.559	2.283	3.081
SN3_substhink	4.139	4.927	4.405	5.477
AF1_stress	3.656	3.674	2.590	3.740
AF2_comfort	3.716	4.261	3.207	4.124
AF3_enjoyold	4.775	4.838	3.664	5.025
CI1_oldbest	4.288	4.247	3.129	4.115
CI2_oldeff	4.212	4.263	3.360	4.432
CI3_oldworks	4.078	4.274	3.328	4.182
RI1_support	5.360	5.620	4.584	6.463
RI2_cooper	6.129	6.391	5.065	5.847
RI3_intendcomply	4.902	5.058	3.711	5.040

RI4_notneed	4.475	5.528	4.543	6.061

	CH1_orgpract	CH2_collchng	CH3_indvchng	BS1_mgrchat
CH1_orgpract	7.278			
CH2_collchng	6.133	6.938		
CH3_indvchng	5.724	5.784	7.558	
BS1_mgrchat	6.161	5.920	5.247	9.364
BS2_collegchat	5.657	5.463	5.190	5.899
BS3_peerhelp	5.562	5.594	4.753	7.015
BS4_mgmtexp	4.546	4.346	4.046	4.891
NE1_srvision	4.132	4.591	4.226	3.673
NE2_exechelp	4.586	4.468	4.283	6.132
NE3_groupchng	5.131	5.077	5.031	5.701
LA1_oldadv	2.949	3.509	2.942	4.671
LA2_oldeff	3.759	3.938	3.460	5.212
TC1_switchtime	3.777	3.971	3.889	5.603
TC2_losework	3.031	3.133	2.957	4.385
TC3_hassle	3.195	3.271	2.910	4.682
TC4_effortworth	4.728	5.117	5.369	5.417
TC5_noteasy	1.673	2.004	2.434	1.671
SN1_colleagthink	5.041	5.229	5.085	5.910
SN2_mgrthink	3.778	4.086	4.067	3.140
SN3_substhink	4.868	4.896	4.640	5.937
AF1_stress	4.009	4.138	4.341	4.016
AF2_comfort	4.327	4.764	4.934	4.482
AF3_enjoyold	4.279	4.870	4.732	4.979
CI1_oldbest	4.433	4.706	4.476	4.539
CI2_oldeff	4.603	5.038	4.842	4.594
CI3_oldworks	4.227	4.624	4.141	4.578
RI1_support	5.418	5.406	5.469	6.217
RI2_cooper	5.503	5.954	5.518	6.703
RI3_intendcomply	4.875	5.522	5.165	5.258
RI4_notneed	5.266	5.030	5.342	6.639

	BS2_collegchat	BS3_peerhelp	BS4_mgmtexp	NE1_srvision
BS2_collegchat	8.404			
BS3_peerhelp	6.242	10.058		
BS4_mgmtexp	3.856	5.415	8.040	
NE1_srvision	4.151	3.856	4.343	7.758
NE2_exechelp	4.722	6.162	5.451	3.615
NE3_groupchng	4.025	5.367	5.757	5.027
LA1_oldadv	3.318	4.970	4.422	2.509
LA2_oldeff	3.051	4.883	4.858	3.223
TC1_switchtime	3.767	4.992	4.206	3.006
TC2_losework	3.225	4.188	4.162	3.331
TC3_hassle	3.729	4.190	4.210	2.349
TC4_effortworth	4.437	5.107	4.136	4.184
TC5_noteasy	2.605	2.113	1.691	1.918
SN1_colleagthink	3.759	5.260	4.904	4.450
SN2_mgrthink	3.428	3.212	2.554	4.439
SN3_substhink	4.382	4.915	4.796	4.098
AF1_stress	3.980	2.904	2.844	3.785
AF2_comfort	4.113	3.651	3.567	4.080
AF3_enjoyold	4.298	4.451	4.095	4.723
CI1_oldbest	4.540	3.551	3.427	4.407

CI2_oldeff	4.544	3.898	3.482	4.378
CI3_oldworks	4.305	3.616	3.371	4.259
RI1_support	4.525	5.871	5.154	5.034
RI2_cooper	5.309	5.258	4.993	5.591
RI3_intendcomply	4.108	4.157	3.577	5.053
RI4_notneed	4.674	6.213	5.290	5.035

	NE2_exechelp	NE3_groupchng	LA1_oldadv	LA2_oldeff
NE2_exechelp	7.665			
NE3_groupchng	5.724	8.130		
LA1_oldadv	4.575	4.075	8.445	
LA2_oldeff	4.545	4.550	6.454	8.260
TC1_switchtime	5.050	4.230	5.246	5.805
TC2_losework	3.492	4.015	4.522	4.747
TC3_hassle	4.553	4.069	5.651	5.615
TC4_effortworth	4.801	5.039	5.495	5.888
TC5_noteasy	1.788	1.819	3.021	3.786
SN1_colleagthink	5.029	5.708	4.519	4.872
SN2_mgrthink	2.560	2.937	1.366	1.822
SN3_substhink	4.284	4.982	4.821	5.128
AF1_stress	2.784	3.296	2.818	3.183
AF2_comfort	3.355	4.031	3.710	3.963
AF3_enjoyold	4.207	4.822	4.600	4.918
CI1_oldbest	3.037	3.833	3.130	3.299
CI2_oldeff	3.397	3.933	3.263	3.624
CI3_oldworks	3.683	3.931	3.795	3.875
RI1_support	5.355	5.901	5.810	6.240
RI2_cooper	5.285	5.975	4.633	4.923
RI3_intendcomply	3.908	5.028	4.033	4.418
RI4_notneed	5.440	6.184	5.631	6.247

	TC1_switchtime	TC2_losework	TC3_hassle	TC4_effortworth
TC1_switchtime	7.507			
TC2_losework	4.789	6.778		
TC3_hassle	5.633	4.581	8.330	
TC4_effortworth	5.743	4.311	5.578	8.602
TC5_noteasy	3.382	2.894	3.839	4.092
SN1_colleagthink	4.454	4.065	3.953	4.883
SN2_mgrthink	1.972	2.168	0.891	2.626
SN3_substhink	4.949	3.457	4.385	5.801
AF1_stress	3.674	3.366	2.618	4.752
AF2_comfort	4.595	3.732	3.167	5.257
AF3_enjoyold	5.011	4.718	3.874	5.908
CI1_oldbest	3.585	4.242	2.771	4.723
CI2_oldeff	4.283	3.872	3.155	5.257
CI3_oldworks	4.329	3.907	3.250	4.971
RI1_support	5.484	4.787	4.472	6.427
RI2_cooper	5.027	4.765	3.788	5.709
RI3_intendcomply	4.204	3.591	2.773	5.481
RI4_notneed	6.477	5.371	5.464	6.801

	TC5_noteasy	SN1_colleagthink	SN2_mgrthink	SN3_substhink
TC5_noteasy	6.240			
SN1_colleagthink	1.939	7.574		
SN2_mgrthink	1.093	3.908	5.889	
SN3_substhink	1.995	5.325	2.801	8.193

AF1_stress	2.504	4.063	2.776	4.029
AF2_comfort	3.307	4.582	2.915	4.593
AF3_enjoyold	3.570	4.984	3.067	4.767
CI1_oldbest	3.005	4.315	3.888	4.341
CI2_oldeff	3.043	4.322	3.804	4.705
CI3_oldworks	3.057	4.449	3.530	4.617
RI1_support	2.983	6.270	3.625	6.018
RI2_cooper	3.068	6.139	4.113	5.455
RI3_intendcomply	3.094	5.709	3.896	4.441
RI4_notneed	2.828	5.557	3.062	5.691

	AF1_stress	AF2_comfort	AF3_enjoyold	CI1_oldbest
AF1_stress	6.228			
AF2_comfort	5.100	7.174		
AF3_enjoyold	5.355	6.183	7.473	
CI1_oldbest	4.971	5.194	5.728	6.930
CI2_oldeff	4.978	5.488	5.826	5.596
CI3_oldworks	4.848	5.304	5.943	5.733
RI1_support	4.909	5.320	6.318	4.982
RI2_cooper	5.557	6.142	6.923	5.846
RI3_intendcomply	5.129	5.478	6.095	5.229
RI4_notneed	4.340	5.355	5.837	4.746

	CI2_oldeff	CI3_oldworks	RI1_support	RI2_cooper
CI2_oldeff	6.777			
CI3_oldworks	5.658	6.995		
RI1_support	5.569	5.580	8.889	
RI2_cooper	5.982	6.171	7.524	9.400
RI3_intendcomply	5.560	5.742	7.245	7.846
RI4_notneed	4.930	4.857	7.314	6.173

	RI3_intendcomply	RI4_notneed
RI3_intendcomply	8.649	
RI4_notneed	5.632	9.922

Item and Total Statistics

Variable	Total Count	Mean	StDev
IM1_manvals	104	5.59	2.59
IM2_commit	104	5.63	2.72
IM3_equal	104	5.12	2.59
IM4_vision	104	5.24	2.74
CH1_orgpract	104	5.56	2.70
CH2_collchng	104	5.88	2.63
CH3_indvchng	104	5.73	2.75
BS1_mgrchat	104	5.23	3.06
BS2_collegchat	104	5.56	2.90
BS3_peerhelp	104	5.02	3.17
BS4_mgmtexp	104	5.13	2.84
NE1_srvision	104	6.40	2.79
NE2_exechelp	104	5.18	2.77
NE3_groupchng	104	5.08	2.85
LA1_oldadv	104	5.04	2.91
LA2_oldeff	104	5.05	2.87
TC1_switchtime	104	5.41	2.74
TC2_losework	104	5.81	2.60

TC3_hassle	104	4.74	2.89
TC4_effortworth	104	5.50	2.93
TC5_noteasy	104	5.20	2.50
SN1_colleagthink	104	5.63	2.75
SN2_mgrthink	104	7.07	2.43
SN3_substhink	104	5.36	2.86
AF1_stress	104	6.43	2.50
AF2_comfort	104	5.97	2.68
AF3_enjoyold	104	6.30	2.73
CI1_oldbest	104	6.64	2.63
CI2_oldeff	104	6.74	2.60
CI3_oldworks	104	6.77	2.64
RI1_support	104	5.65	2.98
RI2_cooper	104	6.19	3.07
RI3_intendcomply	104	6.39	2.94
RI4_notneed	104	5.51	3.15
Total	104	193.77	72.90

Cronbach's Alpha

Alpha
0.9792

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
IM1_manvals	188.18	70.80	0.8008	0.9140	0.9784
IM2_commit	188.13	70.69	0.8056	0.8760	0.9783
IM3_equal	188.65	70.92	0.7557	0.8681	0.9785
IM4_vision	188.53	70.58	0.8411	0.8300	0.9782
CH1_orgpract	188.21	70.75	0.7905	0.8528	0.9784
CH2_collchng	187.88	70.68	0.8368	0.8861	0.9782
CH3_indvchng	188.04	70.77	0.7659	0.8091	0.9785
BS1_mgrchat	188.54	70.43	0.7978	0.8460	0.9784
BS2_collegchat	188.21	70.85	0.6961	0.8044	0.9788
BS3_peerhelp	188.75	70.63	0.7053	0.7772	0.9788
BS4_mgmtexp	188.63	70.86	0.7093	0.7409	0.9787
NE1_srvision	187.37	70.97	0.6811	0.7362	0.9788
NE2_exechelp	188.59	70.81	0.7469	0.8225	0.9786
NE3_groupchng	188.69	70.65	0.7823	0.8131	0.9784
LA1_oldadv	188.73	70.94	0.6618	0.7598	0.9789
LA2_oldeff	188.72	70.78	0.7296	0.8214	0.9786
TC1_switchtime	188.36	70.79	0.7607	0.8476	0.9785
TC2_losework	187.96	71.06	0.6985	0.7510	0.9787
TC3_hassle	189.03	71.04	0.6335	0.7810	0.9790
TC4_effortworth	188.27	70.50	0.8100	0.8226	0.9783
TC5_noteasy	188.57	71.67	0.4782	0.6967	0.9795
SN1_colleagthink	188.13	70.64	0.8129	0.8218	0.9783
SN2_mgrthink	186.70	71.50	0.5668	0.7255	0.9792
SN3_substhink	188.41	70.70	0.7614	0.7760	0.9785
AF1_stress	187.34	71.07	0.7258	0.7753	0.9787

AF2_comfort	187.80	70.82	0.7697	0.8303	0.9785
AF3_enjoyold	187.47	70.57	0.8469	0.9072	0.9782
CI1_oldbest	187.13	70.87	0.7614	0.8441	0.9785
CI2_oldeff	187.03	70.79	0.8025	0.8447	0.9784
CI3_oldworks	187.00	70.82	0.7807	0.8183	0.9784
RI1_support	188.12	70.28	0.8746	0.9068	0.9780
RI2_cooper	187.58	70.24	0.8605	0.9110	0.9781
RI3_intendcomply	187.38	70.59	0.7753	0.8945	0.9784
RI4_notneed	188.26	70.34	0.8035	0.8288	0.9783

* NOTE * Maximum rows or columns exceeded for MATRIXPLOT.

Appendix D: Pixel Representations and Dimensional Slopes of Survey Responses


app119.jpg
app120.jpg
app121.jpg
app122.jpg
app123.jpg
app124.jpg
app125.jpg
FDGraph_APP2.jpg
FDGraph_app3.jpg
FDGraph_app4.jpg
FDGraph_app5.jpg
FDGraph_app6.jpg
FDGraph_app7.jpg
FDGraph_APP8.jpg
FDGraph_app9.jpg
FDGraph_app10.jpg
FDGraph_app11.jpg
FDGraph_app12.jpg
FDGraph_app13.jpg
FDGraph_app14.jpg
FDGraph_app15.jpg
FDGraph_app16.jpg
FDGraph_app17.jpg
FDGraph_app18.jpg
FDGraph_app19.jpg
FDGraph_app20.jpg
FDGraph_app21.jpg
FDGraph_app22.jpg
FDGraph_app23.jpg
FDGraph_app24.jpg
FDGraph_app25.jpg
FDGraph_app26.jpg
FDGraph_app27.jpg
FDGraph_app28.jpg
FDGraph_app29.jpg
FDGraph_app31.jpg
FDGraph_app32.jpg
FDGraph_app33.jpg
FDGraph_app34.jpg
FDGraph_app35.jpg
FDGraph_app36.jpg
FDGraph_app37.jpg
FDGraph_app38.jpg
FDGraph_app39.jpg
FDGraph_app40.jpg
FDGraph_app41.jpg
FDGraph_app42.jpg
FDGraph_app43.jpg
FDGraph_app44.jpg
FDGraph_app45.jpg
FDGraph_app46.jpg
FDGraph_app47.jpg
FDGraph_app48.jpg
FDGraph_app49.jpg
FDGraph_app50.jpg
FDGraph_app51.jpg
FDGraph_app52.jpg
FDGraph_app53.jpg
FDGraph_app54.jpg
FDGraph_app55.jpg
FDGraph_app56.jpg
FDGraph_app57.jpg
FDGraph_app58.jpg
FDGraph_app59.jpg
FDGraph_app60.jpg
FDGraph_app61.jpg
FDGraph_app62.jpg
FDGraph_app63.jpg
FDGraph_app64.jpg
FDGraph_app65.jpg
FDGraph_app66.jpg
FDGraph_app67.jpg
FDGraph_app68.jpg
FDGraph_app69.jpg
FDGraph_app70.jpg
FDGraph_app71.jpg
FDGraph_app72.jpg
FDGraph_app73.jpg
FDGraph_app74.jpg
FDGraph_app75.jpg
FDGraph_app76.jpg
FDGraph_app77.jpg
FDGraph_app78.jpg
FDGraph_app79.jpg
FDGraph_app80.jpg
FDGraph_app81.jpg
FDGraph_app82.jpg
FDGraph_app83.jpg
FDGraph_app84.jpg
FDGraph_app85.jpg
FDGraph_app86.jpg
FDGraph_app87.jpg
FDGraph_app88.jpg
FDGraph_app89.jpg
FDGraph_app90.jpg
FDGraph_app91.jpg
FDGraph_app92.jpg
FDGraph_app93.jpg
FDGraph_app94.jpg
FDGraph_app95.jpg
FDGraph_app96.jpg
FDGraph_app97.jpg
FDGraph_app98.jpg
FDGraph_app99.jpg
FDGraph_app100.jpg
FDGraph_app101.jpg
FDGraph_app102.jpg
FDGraph_app103.jpg
FDGraph_app104.jpg
FDGraph_app105.jpg
FDGraph_app106.jpg
FDGraph_app106.png
FDGraph_app107.jpg
FDGraph_app108.jpg
FDGraph_app109.jpg
FDGraph_app110.jpg
FDGraph_app111.jpg
FDGraph_app112.jpg
FDGraph_app113.jpg
FDGraph_app114.jpg
FDGraph_app115.jpg
FDGraph_app116.jpg
FDGraph_app117.jpg
FDGraph_app118.jpg
FDGraph_app119.jpg
FDGraph_app120.jpg
FDGraph_app121.jpg
FDGraph_app122.jpg
FDGraph_app123.jpg
FDGraph_app124.jpg
FDGraph_app125.jpg
FDGraph_jpg30.jpg

Appendix E: Linear Regression results for $FD_{pixel\ proximity}$ vs OC success

Coefficients Table for the Regression of OC Success as the Dependent Variable and $FD_{pixel\ proximity}$ as the Independent Variable

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-29.935	2.779		-10.773	<.001		
	D(Pixel Proximity)	20.651	1.632	.753	12.651	<.001	1.000	1.000

a. Dependent Variable: Mean(OC Success)

The regression equation is: Mean Success = -29.94 + 20.65 $D_{pixel\ proximity}$.

Model Summary for the Regression of OC Success as the Dependent Variable and $FD_{pixel\ proximity}$ as the Independent Variable

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.753[a]	.567	.564	1.78796	.567	160.051	1	122	<.001	1.989

a. Predictors: (Constant), D(Pixel Proximity)

b. Dependent Variable: Mean(OC Success)

ANOVA for the Regression of OC Success as the Dependent Variable and $FD_{pixel\ proximity}$ as the Independent Variable

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	511.650	1	511.650	160.051	<.001[b]
	Residual	390.009	122	3.197		
	Total	901.659	123			

a. Dependent Variable: Mean(OC Success)

b. Predictors: (Constant), D(Pixel Proximity)

Appendix F: Linear Regression results for $FD_{replication}$ vs OC success

Coefficients for the Regression of OC Success as the Dependent Variable and $FD_{replication}$ as the Independent Variable

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-1.578	.505		-3.125	.002		
	D(replication)	5.875	.420	.785	13.982	<.001	1.000	1.000

a. Dependent Variable: Mean(OC Success)

The regression equation is: Mean Success = -1.58 + 5.88 Dreplication

Model Summary for the Regression of OC Success as the Dependent Variable and $FD_{replication}$ as the Independent Variable

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.785[a]	.616	.613	1.68524	.616	195.483	1	122	<.001	1.720

a. Predictors: (Constant), D(replication)

b. Dependent Variable: Mean(OC Success)

ANOVA for the Regression of OC Success as the Dependent Variable and $FD_{replication}$ as the Independent Variable

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	555.176	1	555.176	195.483	<.001[b]
	Residual	346.483	122	2.840		
	Total	901.659	123			

a. Dependent Variable: Mean(OC Success)

b. Predictors: (Constant), D(replication)

Appendix G: Normality of FD as a Function of Success

Normality of Dimensional Response as a function of CS3 success rating

Success level CS3	Normality of FD by Pixel method for a given success level					Normality of FD by replication method for a given success level				
	Mean FD by Pixel	StDev (D)Pixel	N	AD	P	Mean FD by replication	StDev (D)replication	N	AD	P
0	1.623	0.1914	3	0.264	0.37	0.8931	0.5463	3	0.189	0.631
1	1.54	0.1474	6	0.315	0.416	0.6083	0.5365	6	0.368	0.297
2	1.619	0.06949	11	0.51	0.153	0.8226	0.1768	11	0.387	0.323
3	1.635	0.04596	15	0.304	0.529	0.8877	0.1603	15	0.289	0.565
4	1.646	0.09878	19	2.393	<0.005	0.9377	0.3703	19	2.719	<0.005
5	1.722	0.02824	13	0.617	0.085	1.196	0.0856	13	0.5	0.17
6	1.745	0.02997	15	0.548	0.131	1.306	0.09441	15	0.329	0.477
7	1.763	0.0281	13	0.504	0.166	1.433	0.1062	13	0.641	0.073
8	1.781	0.03841	22	3.196	<0.005	1.452	0.1421	22	2.676	<0.005
9	1.81	0.01732	3	0.488	0.057	1.577	0.05575	3	0.43	0.093
10	1.803	0.01528	3	0.23	0.487	1.597	0.03898	3	0.376	0.144
NA	*	*	1	*		*	*	1	*	

Note: Red numbers indicate OC success levels that do not appear to be normally distributed to the 95% level of confidence.

Appendix H: Social Media Recruitment Splash Page