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Change in Organizations, What Do They Have to Say About It? Machine Learning Testing of an Affective Behavioral Circumplex Model of Reactions to Change

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CHANGE IN ORGANIZATIONS, WHAT DO THEY HAVE TO SAY ABOUT IT?
MACHINE LEARNING TESTING OF AN AFFECTIVE BEHAVIORAL
CIRCUMPLEX MODEL OF REACTIONS TO CHANGE

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
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Doctor of Philosophy
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by
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ABSTRACT

The ability for organizations to effectively systematically change their culture is becoming increasingly necessary. These changes are often implemented through a strategic process to which employee reactions have a great impact on their success. This study tested a new affective behavioral circumplex model of reactions to change. Although that was not fully supported, the data clusters that did emerge held true across samples. Not only did this study test this new model but also used new methods in Machine learning to examine qualitative responses which were found to be accurate and reliable. Furthermore, this study examined how this model is associated with additional contexts through theoretically related survey questions.

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CHAPTER ONE

INTRODUCTION

The ability for organizations to effectively systematically change their culture is becoming increasingly necessary as the world is continuously changing through aspects such as globalization, technological advancements, and increased competition (Jaros, 2010). These contextual changes can require an organization to change and adapt to survive. One of the biggest examples of an external source is the rise of the internet. Instantly, communication was significantly faster, more detail could be shared with those further away, and overall workforce competencies and requirements vastly changed. Organizations had to adjust to this by forming new policies, interactional rules, and overall structure to use this new technology effectively. External changes are not the only instance where change might be required. For example, imagine procedures that have become norms are efficient but not safe such as not saying a patient's name in a hospital and then doing a procedure on the wrong patient. In this scenario, the culture of an organization needs to change to ensure the safety of workers and consumers.

As is evident, the ability for organizations to change is important; however, change efforts are often unsuccessful with failure estimates ranging from 28-93%, with many hovering around 70% (Decker et al., 2012; Candido & Santos, 2008; Wong, Chau, Scarbrough, & Davidson, 2005; Candidto & Santos 2015, Kotter, 1995). Therefore, it is vital for the overall process to be studied with a close examination on what is potentially contributing to this high failure rate to develop solutions for these dilemmas.

This dissertation intends to explore organizational change and the impact of change reactions though a new affective circumplex model of change by using novel

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methods. To begin, it's important to review the process of how organizations experience changes.

CHAPTER TWO

CHANGE IN ORGANIZATIONS

Making a change in an organization is typically thought of as a process that contains three segments which we will explore in depth. Lewin (1947) created the original model that became influential in this context for a multitude of future models. Lewin's categorization started with unfreezing, which is the basis of "preparing for the change"; moving, which would correspond with "implementing the change", and freezing, which would align with "sustaining the change". Armenakis and Bedeian (1999) reviewed concepts related to change and how they fit into these phases of change with .multiple different models and descriptions of the change process. Although these different models can vary with how many steps or pieces are involved, they frequently follow the line of preparing for the change, implementing the change, and sustaining the change. From this original model there have been many iterations over the years. To review a few models, Judson (1991) came up with a model containing five different parts. His beginning stage of analyzing and planning the change would fit into "preparing for change". For "implementing the change", three of his designations fit (i.e., communicating the change). Finally, for "sustaining the change", his last component of consolidating and institutionalizing the new state is applicable. Kotter (1995) expanded upon this and had eight different phases where three parts fit into "preparing for change" (i.e., establishing a sense of urgency based on the environment), two facets associated

with "implementing the change"(i.e.,. communicating the vision through numerous channels), and the last three for "sustaining the change" (i.e., publicizing wins and successes of the change). Gaplin (1996) expanded this further and had a nine-factor model. Seven of these factors fit into the "preparing for change" category, (e.g. developing and disseminating a vision of planned change), one fit into the "implementation of change category", (e.g. rolling out the recommendations), with the final factor involving "sustaining the change" (e.g. measuring, reinforcing, and refining the change). These are just a few examples on how even though these models have various shapes and sizes; they frequently fit under three general categories. To fully characterize the change process, this study will expand upon these change theories further.

Change Process

Preparing for change

In "preparing for change", unfreezing the already existing organizational culture and planning for the change are key aspects. It is necessary to develop a clear understanding of the current organizational change based on three levels of culture. What are the artifacts, espoused beliefs, values, and basic assumptions that characterize the organization (Schein, 2010)? Furthermore, the future changed desired states of each level must be specified (Higgs & Rowland, 2010). Once those are established, the differences between the two need to be determined (Higgs & Rowland, 2010). Along with those differences, the reasoning behind those changes needs to be clearly defined and supported. The need for change has to be established (Galpin, 1996) and relating external

influences, such as crises and opportunities, to this change helps reinforce the reasoning (Kotter, 1995). Along with that, the actual structural factors of the change need to be determined and reviewed by a group of individuals devoted to the change (Judson, 1991; Kotter, 1995). These stakeholders are vital to the process as they are part of what creates buy-in and facilitates the implementation over the appropriate groups. When making a plan of action for change, there needs to be a determination made whether the change process going to be episodic or continuous and which would best fit with their culture and change goals (Weik & Quinn,1999). Episodic change refers to organizational changes that tend to be infrequent, discontinuous, and intentional; while continuous change relates to organizational changes that tend to be ongoing, evolving, and cumulative (Weick & Quinn, 1999). There are also multiple interpersonal aspects that can arise as an issue at this phase. This is when anticipation and denial from organization members can come into play (Jaffe, Scott, & Tobe 1994; Isabella,1990). As typically there is reasoning behind a change, members can preemptively perceive the upcoming change and begin to have an initial reaction. As employees' reactions are an integral part of the process, and where we look to explore in this study, these will be reviewed in depth in the following section.

<center>Implementing change</center>

Next in this process is implementing change and moving the organization through the actual application and adjustments. This is where a plan goes into action. The content and necessity of the change needs to be communicated through numerous systematic communication channels (Judson, 1991). Overall structures, systems and

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policies need to be transformed to facilitate the change (Kotter, 1995). Additionally, as part of the content of the change, the behaviors desired to reach the goals for the initiative need to be defined (Schein, 2010). Previous research has found that this is the point when individuals in an organization associate events with previous experiences and they culminate the comparison of these before and after change (Jaffe, et al., 1994) or begin to resist change (Isabella, 1990) as frequently people are not welcoming to just any change (Buchanan, et al. 2005). There are certain individual states that help employees accept and begin to incorporate this change. Armenakis, Harris, and Field (1999) state that it is helpful for individuals to feel the urgency and need of change or discrepancy; they have the ability to actually change or self-efficacy; personal drive or valence to change; perceived support for the change; activities that are symbolic of the change; knowledge of what is required of them or best practices; and management of information and formal support. Along with these states, Schein (2010) mentions that for change to occur there must be level of psychological safety. For this to come about, Schein states that 8 things must happen some of which tie into some of the same ideas formed by Armenakis and colleagues (1999). A compelling positive vision, formal training, involvement of the learning, informal training of relevant family group and teams, practice fields, coaches and feedback, positive role models, support groups in which learning problems can be aired and discussed, and systems and structures that are consistent with the new way of thinking and working. Once these criteria are met and change occurs, a new complication arises; sustaining that change.

Sustaining Change

The last step in creating change is to freeze the adjustment into everyday occurrences. This is where many changes often fail. Initiatives might have all of the good intentions of succeeding but might lose momentum and urgency overtime and, therefore fade. Organizational change initiatives typically either change, grow, or terminate over time (Van de Ven & Huber, 1990). Buchanan and colleagues (2005) reviewed the sustaining change literature and discuss complications with this process, highlighting some of the following processes and theories. Cummings and Worley (1997) commented that often change initiatives do not persevere and potentially last only until goals have been reached. However, Jacobs (2002) stipulated five different aspects of sustaining change. His research suggested change needs to be substantial (is it consistent?), individual (are the people competent, committed to the change and being rewarded appropriately?), leadership driven (leaders have clear, consistent, and challenging goals and behaviors?), processual (are continuous backers support, monitoring and control involved?), and contextual (is there agreement of the change with inside and outside forces?). To meet this success in change, it is important to constantly evaluate the success of the varying aspects of the initiative and how they are working in the company (MacKay & Chia, 2013). Rimmer and colleagues (1996) found the sustainability of change to be largely impacted by social contexts from all levels of stakeholders in the organization from CEOs to front-line workers. The last two facets of Judson's (1991) model apply to this context. Once the change has been accepted, the behaviors and norms need to become a desired state and, along the way, the new state needs to be consolidated

and institutionalized. Kotter (1995) includes at the beginning of the change right after implementation the organization needs to plan for and acknowledge short term wins of the change, reinforcing the movement, and continuously consolidating improvements, along with finally institutionalizing the change by associating the organizations successes with the change effort.

Considering all of these facets is crucial when working to make changes happen and stick in an organization. As seen in the reviewed research One piece of this information of that has been a theme throughout all of these actions is that's it is vital to understand is the impact of how employees are reacting to the change. They are the placers the ground making changes happen.

<center>Reactions to Change</center>

<center>Reactions to Organizational Change</center>

As has been highlighted, the impact of employees in the process of making changes is a critical make-or-break factor. Their level of support and commitment to the change in conjunction with the level of support the organization provides is significantly related to the change success (Meyer, Srinivas, Jaydeep, Lal, & Topolnytsky, 2007; Cullen, Edwards, Casper, & Gue, 2014). These employees' reactions and actions are based on a great multitude of factors which this study will a sample of those consideration.

Change reactions, along with the change process, can often be viewed in three parts. There are antecedents such as individual and situational differences, the reactions that can fall into buckets like affective, cognitive, and behavioral, and lastly the outcomes

of these reactions such as work and personal consequences. Oreg, Vakola, and Armernakis, (2011) laid out this process and through a review of 79 different quantitative studies (see figure 2.1). We will now touch on some of the findings and insights of these studies.
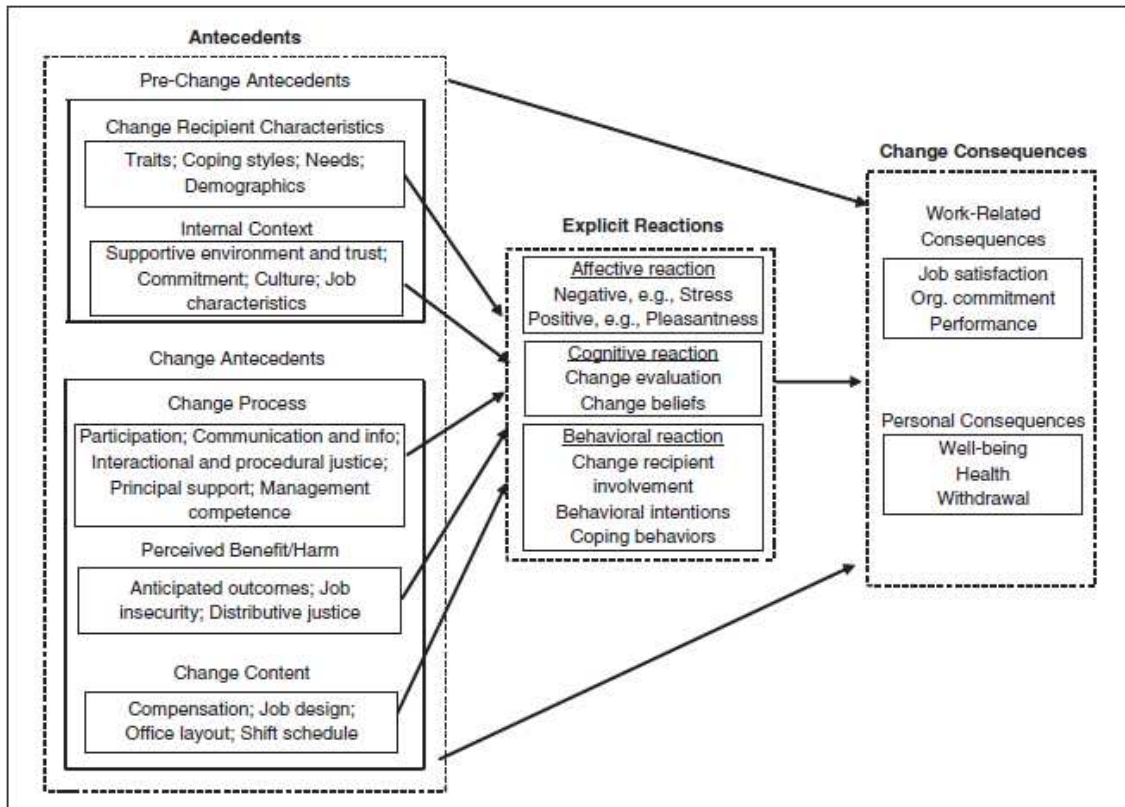
Figure 2.1: Antecedents, explicit reactions, and change consequences of organizational change

Change reaction antecedents start the whole process of reacting to change. These can be split up into pre change antecedents and then the antecedents to the actual change. Pre change antecedents are not related to the change but are specifically characteristics of individuals and the environment that currently exist. These can include individual

differences that can be theoretically related to change, such as personality traits, coping styles, needs and demographics. Certain personality traits have been studied in more depth such as locus of control and self-efficacy as reviewed in depth by Vakola, Armenakis, and Oreg (2013). Locus of control is related to how an individual views how much control they have over the world. Internal locus of control involves an individual thinking that they have control over the actions and changes that happen in the world; whereas external locus of control involves individuals thinking that control over events and changes lies outside of being affected by their personal actions (Rotter 1966). For example, during times of insecurity such as change, having a greater internal locus of control vs an external locus of control can reduce negative emotional reactions (Naswall, Sverke, & Hellgren, 2005) There have also been personal characteristics such as tolerance of ambiguity, self-esteem, coping styles, and the big five, more specifically openness to experience, and neuroticism (Vakola, Armenakis, & Oreg, 2013). Other individual differences have been explored but not frequently found to be impactful e.g. demographics.

In addition to the individual based pre-change antecedents that are theorized, there is also the organizational internal context. The organization type and factors that individuals work in impacts every facet in their day-to-day work and how things get done. Some factors that can impact change reactions include, level of support in the environment, andculture of commitment (leading to increased success; Shum, Bove, & Auh, 2008). Additionally, looking at how much trust is a part of the environment, does the organization commit and follow through? As well as different characteristics of the

job and their demands (higher ability to make decisions resulting in higher readiness for change; Meyer, Srinivas, Jaydeep, Lal, & Topolnytsky, 2007; Cullen, Edwards, Casper, Gue, 2014; Jaffe, et al., 1994; Cunningham, et al., 2002)

Along with pre-change antecedents, there are change reaction antecedents. These are more specifically focused to the change, whereas the pre-change antecedents were focused on the overall environment (organization and individual trait/states). Some of these factors include: what the change processes are, what the change content is, and is there perceived benefit or harm? For the change process, this can involve what an individual does in preparing for and working through the change. It additionally can involve what the organization does such as how they communicate change-based information (e.g. through what methods and how clear communications are). A clear area where the impact of change process shows up is the actions and policies of the change being rolled out in an interactionally and procedurally just way (Kikul, Lester, & Finkl, 2002). Along with the processes being just, a huge part of the process is if they have good support from leaders at multiple levels in the organization (Koivisto, Lipponen, & Platow, 2013; Bernerth, Armenakis, Field, & Walker, 2007). These leaders actually being able to support the change and take actions that lead the implementation successfully is key (Abrell-Vogel, Rowold, 2014; Salmela, Erikson, & Fagerstrom, 2012). Something else employees consider is perceived benefits/harm which relates to beliefs about the outcomes from the change. When big changes are happening, especially with mergers and acquisitions that might result in layoffs (Smeltzer & Zener, 1992), there are often concerns around job security or how their actions might impact that. Along with job

concerns, employees also get worried about how distributivity just decisions are. They can wonder if the job focused decisions might be more favorable to someone familiar compared to more skilled (Brockner, 1990; Chang 2002).

An additional piece that can have an impact on change reactions is type of change. Varying types of change can result in different reactions from different people (Buchanan, et al. 2005). For example, if it's related to changing the management levels of an organization, for those that like the change or think that it's an area that should be addressed then that makes a difference. Additionally, things like office layout could have a positive reaction from someone Who exhibit high social tendencies and enjoy interaction with coworkers (Haynes, 2008).

After reviewing these factors, it is clear that there are many contexts and interactive constructs that contribute to employee change reactions. Continuing with how change impacts the employees, reactions for individuals typically have been measured in three categories: affective, cognitive and behavioral. Affective reactions can usually range from negative to positive reactions. The negative reactions can be things like stress or change anxiety (Baron,1990). Some positive reactions can be experiences like feeling pleasantness and satisfaction (De Dreu & Van Vianen, 2001). Cognitive reactions can include factors like change evaluations (e.g. change efficacy or change beliefs) (Tichy, 1974).

 Behavioral reactions include a few different types of actions. For example, this could be displayed through getting involved in the change and working to drive it forward. Another side of this that is still connected to behavioral reactions is through

intentions. Behavioral intentions can involve the internal behavioral or planning process like intending to attend a change information session (Webb & Sheeran, 2006). Another example that is behavioral in nature is an individual producing coping behavior to manage emotions or reorienting tasks which can often be a reaction from the stress of change (Anderson, 1977).

These change reactions and antecedents have outcomes which are viewed as the consequences of change. Antecedents can relate directly to outcomes or reactions mediate or moderate their impact on the change. There is a vast amount of change consequences, these can have different subjects, two of the most common being work related consequences and personal consequences. Work related consequences are work related impacts from an individual. These can include how satisfied a person is with their job, how committed to the organization they are, which has also been related to change success (Vakola & Nikolaou, 2005), how likely they are to turnover and leave the organization (Bauer & Bender, 2004; Rafferty & Griffin, 2006), it can impact teamwork quality (Alpander & Lee, 1995) and overall performance. Some of the personal consequences can be an individual's well-being, diminished physical and mental health, and their withdrawal from activities and potentially work (Bauer & Bender, 2004; Nelson, Cooper, & Jackson, 1995; Jimmieson, Terry, & Callan, 2004).

<u>A New Model of Change</u>

Since the process of change has such a large impact on individuals at work and there are so many factors and possibilities on how these factors interact, it is important to try to look at comprehensive models. To do this this study will take a deeper look at a

model proposed by Oreg, Bartunek, Lee, and Do (2018) that covers reactions in the context of how they are a central part of change. As this study has reviewed the many reactions to change it's important to look at how they are typically related to outcomes. When discussing change in organizations, it is often framed in how to ensure its success often through looking at employee resistance (Oreg, 2006; Van Dijk & Van Dick, 2009). In a great number of articles, it is an outcome that is seen as reducing the effectiveness of change, whereas the opposite of that is having a positive reaction to change (Bateh, Castaneda, & Farah, 2013). Frequently however, it is primarily passive, such as an individual's reactive state (Oreg, 2006). If someone has a negative attitude through and doesn't put it into behavioral action, how much does that really impact the change initiative's success? There is another layer there of how the activity of those affective reactions impact actual behavior. This goes past Russel's (1980), circumplex model of affect, by tying it to change reactions as well as exploring the context of the behavioral aspect that arise from the affect and valence. To elaborate, affect/valence act in accordance with behavior where when we look at how these interact, they happen through an episode where someone could get a feeling of affect in a negative or positive way, then then feel a level of valence which then results in active or passive behavioral actions (Oreg, et al., 2018). Since these are so closely and quickly tied together, when it comes to practical impact on outcomes, research needs to look towards the behavioral activation aspect in conjunction with affect. Therefore, we look to see how the these combine in employee reactions through change and their impact.

When looking at the positivity to negativity scale, examples of the positive end include: enthusiasm, inspiration, optimism, contentment, and happiness (Seo, Barrett, & Bartunek, 2004). The negative scale can include anger, displeasure, nervousness, exasperation, distress, anxiety, or sadness (Watson, Clark, & Tellegen, 1988). Additionally, there is the activity scale, passive reactions include characteristics such as calm or apathetic, whereas examples of high activation responses are excited and angry (Seo et al., 2004).

To further dive into how these factors work together to characterize reactions to change we look at how these two factors combine. For example, furious would be negative and more likely result in actions being taken by an employee and they would voice their discontent (Oreg, 2006; O'Neill & Lenn, 1995). Similarly, with positive emotions, someone feeling excited could result in a higher likelihood in proactively participating in the change whereas someone feeling content with the change might not have the same implications. With reactions to change ranging from positive to negative and from active to passive, Oreg et al. 2018 proposed a circumplex model of change reactions that follows the affective circumplex model that Russel (1980) theorized, building upon it to incorporate behavior. With these four quadrants, it is important to define what characteristics they are comprised of. Oreg and colleagues (2018) named these, Change Acceptance, Change Disengagement, Change Resistance and Change Proactivity (see Figure 2.2).
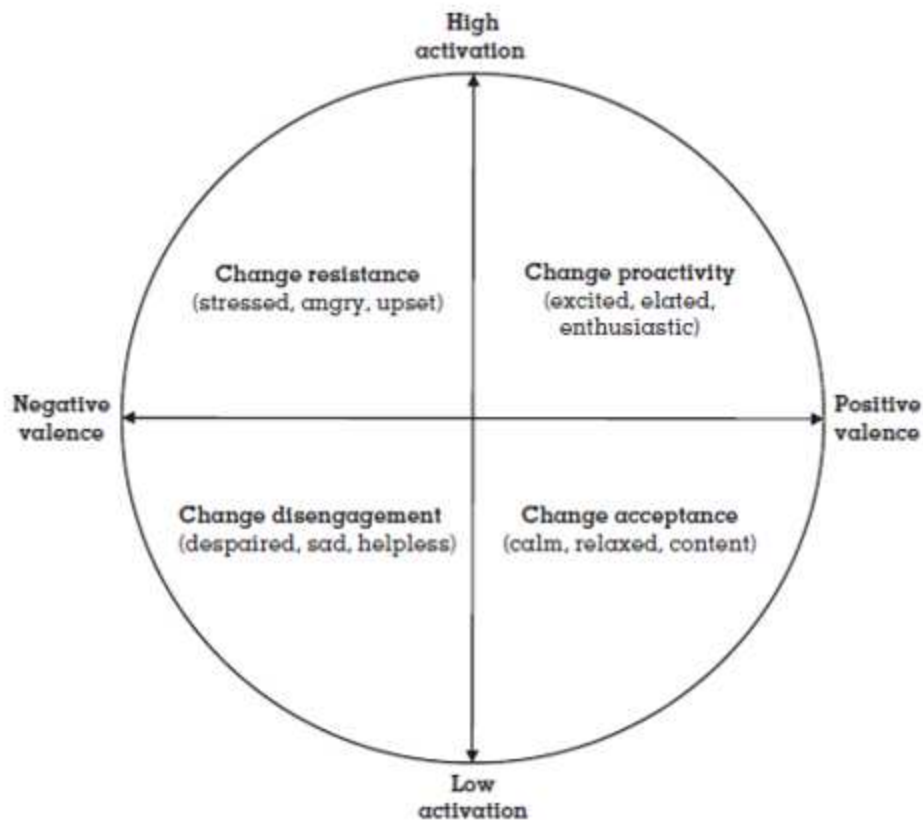
Figure 2.2: Circumplex of Change Recipients' Responses to Change and Underlying Core Affect

Change Acceptance: characterizes passive acceptance, individuals who fall in this quadrant are fine with change. When hearing about a change, these individuals might be welcoming, but not make extra effort to push the changes forward. They also might not put in effort to give feedback or their opinion on the change as much as someone who is more active in their reactions.

Change Disengagement: The negative quadrant that lies across from change acceptance. This is more of a passive dislike, which might involve not fully participating or listening,

or liking the old way of doing things more. Individuals also might not express their dislike of a change or go to efforts to non-participate or influence others.

Change Resistance: is characterized here as "the more active end of change disengagement" This is when individuals are actively negative regarding the change and might voice their distaste for the change. Individuals also might talk to others and try to convince them to not like the change spreading the negative sentiment (O'Neill & Lenn, 1995) They would potentially also actively not participate, choosing to not attend or follow new processes fully when they don't agree with them, making the change more difficult.

Change Proactivity: The quadrant of change reaction that is probably the most desired for businesses implementing change is change proactivity. This type of change involves people who are enthusiastic about the change, they are the ones that would actively participate and encourage others to participate in the change. They will also often give feedback on how to implement it overall as well.

This is such an important concept for many organizations. For example, in this study the organization had rolled out an initiative relates to being present at work and understanding your personal state called conscious leadership (or conscious professionalism). Countless hours and a great deal of stakeholders have been involved with the roll out however there is a belief that there are varying levels of use and feeling about the program in the overall organization. Therefore, looking for how the affectivity and activity of the circumplex appears can vital to driving the program forward.

CHAPTER THREE

TESTING MODELS

<u>Qualitative vs Quantitative Data</u>

To date, Oreg et al. (2018) have only proposed this model. One of the aims of this study is to test this model and see its applicability in practice. There are multiple ways to go about this practice; however, frequently, researchers use existing quantitative scales, or they are developed through careful design and testing through factor analysis. Measures are then tested to see if they are valid by looking at the statistical associations with theoretically related constructs. A benefit of numerical responses is that they are objective, and the specific answer given by the participant does not involve interpretation by the researcher. This does not, however, necessarily uncover some of the rich value that comes from qualitative data (Rahman, 2017). Good tests of models often take multi-method approaches. The obvious alternative to quantitative data is qualitative data – in the survey context this typically takes the form of open-ended questions with natural language responses. Qualitative data, although rich, has its own set of complications. It is usually very time consuming to analyze especially as you get to populations in large organizations. It also can be very subjective and calls for multiple raters to come to appropriate level of interrater reliability. It does however also allow for individuals to express their feelings with more nuance and in a richer (and in a multi-variate sense, broader) way than a set of numerical options where actions and intentions with more context and causation must often be collapsed into one response.

In quantitative research, there is often data collection that can identify directional context and issues with aspects such as priming (when respondents look at the question they can see respond with socially desirable responses). For example, if respondents are looking at a question that is phrased where a positive response would be good (e.g. I like the change) they might put a positive response because they think the org would want to see it that way or they might think that it is not anonymous. When it comes to eliciting individuals' reactions to change and measuring their affective behavioral responses with a qualitative question, it can remove priming toward what the researchers are looking for beyond the subject, as well as also capture the full range of reactions and emotions as they are feeling them without restricting it to a specific state (e.g. feeling satisfied). That is why this study proposes to qualitatively test the circumplex model of change reactions leading to (H1a) evidence of the circumplex model in will be found in the qualitative data.

As we mentioned earlier, typically, working with qualitative data is a very lengthy, subjective process, requiring multiple raters reading every response and rating based off their personal perception. As science has advanced in technology, we are now able to teach computers and machines to learn how words relate to each other and derive meaning from that in a way that matches human natural language processing (Gunther, Rinaldi, & Marelli, 2019). This process also has benefits through mitigating some of those issues that spur from lack in human cognitive ability. From this, using machine learning to understand text data is taking social sciences research by storm. It's already widely used in political science fields, is used greatly in social media analytics, and has

resulted in competitions in academic conferences. In fact, Twitter, historically being one of the most research friendly platforms, has resulted in a great number of processes for working with tweet sized responses with 140-280 characters being shared in open source code platforms. These processes and code for short responses are ideal tools for working with the types of responses to open ended employee surveys, especially with large amounts of data in large organizations. Testing this hypothesis, therefore, fills a greater research benefit, answering the question "Can we use a novel method of analyzing the data and testing to see how responses fit into clusters (e.g. the four quadrants) to find evidence for a model that can be used in future initiatives and research?"

<p align="center">Natural Language Processing</p>

There are a few aspects to consider when looking at natural language processing. A good place to start is looking at language in general. When humans learn language, they connect a set of associations based on what they have learned to derive meaning from the words (Aslin, Saffran, Newport, 1998).

When researchers are using machine learning to analyze natural language processing models, there are different categories: supervised, semi-supervised, reinforcement, or unsupervised. Supervised has a full dataset to work off of to be able to learn what factors help characterize an observation. Semi-supervised involves some parts of a dataset that are labeled and the other aspects it learns by association of characteristics. Reinforcement learning involves learning through trial and error from making a decision and associating characteristics between right and wrong answers to get better. Essentially, reinforcement learning always has an environment where it is given

inputs and learns from trying different outputs improving each time to get to a better outcome in said environment. Unsupervised models don't have labeled observations and involve taking in a great amount of data where then decisions are solely by a mass number of associations (Fumo 2017). Each of these can be of used for a different process. For example, for a classification or regression outcome for defining information, it is better to have a supervised dataset since you know the types of outcomes you're looking to predict and there are predefined right or wrong answers (e.g. is this a recipe for cookies or not (classification), or how much does this house cost (regression)). Semi-supervised and reinforcement learning can also be used for classification with either having some defined data or having info on if the outcome is correct. With unsupervised, this can be better for clustering mass amounts of data you don't know the outcomes for (what are people talking about on the internet) or noticing something out of the ordinary that doesn't fit in with patterns (e.g noticing out of pattern spending for credit card fraud). If we think about our affective circumplex model here we're looking at a type of regression and categorization problem seeing how the responses fit on the continua and set into quadrants through cluster analysis. Therefore, using supervised learning is likely the best method of machine analysis in this domain. Machine learning (ML) models understand and learn from the data by taking the input of X and the identified outcome of Y and learn the relationship between the two to be able to predict an unknown Y based on X (like many traditional statistical models). The way this is done in ML is through the computing system forming heuristic type judgments based on the relationships between the two variables, which is very similar to how human beings process natural language

information. However, this is in a computing system and therefore can factor in many more heuristics and be more systematic than humans (Kahneman & Traversky, 1973). To understand text as we would have it here it is important to understand the meaning of what is provided in responses to an employee survey (e.g. X) to predict Y. To do this through natural language processing it is important to understand the syntax of the words in the responses and then the semantics of how these words related together to form meaning. For syntax, there are many dictionaries of pretrained models for deriving the types of words and this follows a multitude of steps which we will review further as we discuss the method. With semantic analysis this places words on a vector then looks at how close they are and their relationships to each other to make inferences (Castanon, 2015). A popular quote used that describes this idea well is "You shall know a word by the company it keeps" (Firth, 1957, p. 11) "A classic example of this is king – man + woman = queen. In other words, adding the vectors associated with the words king and woman while subtracting man is equal to the vector associated with queen" (Castanon, 2019). As the model takes into account all of these relationships and how that impacts Y, it is able to learn and predict Y. Therefore, we will be using this type of model to understand open ended responses (X) and how they relate to the affective and activity of responses (Y) and if that fits the affective circumplex model.

<u>Study Purpose & Goal</u>

The focus of this study was to examine employee response data for evidence of Oreg and colleagues' (2018) circumplex of affective behavioral reactions to change. The goal of this study is to use two substantially different approaches to do this: natural

language analysis of responses to open-ended questions using machine learning techniques, and analysis of traditional quantitative survey responses. The value of this study will be two-fold: (1) it will provide evidence for or against the circumplex model of employee reactions – if the two samples converge; (2) it will provide new insights into the use of employee reaction data if the two samples come to different conclusions. While this outcome might appear problematic, it actually may provide evidence that improves our understanding of employee reactions and employee reaction measures and how they are interpreted.

Replicability of the Model

One thing that is an important value add for sentiment analysis is how replicable a trained model is. With differing word relationships in a new dataset, there can be issues with replicability if the subject matter is too different. For example, if individuals are referring to two entirely different topics, they might use different phrases to describe something therefore causing the model to be less accurate with coding due to the relationships between words. However, if a question is asked about a similar topic there can be generalizable replicability. With this study we aim to test the generalizability of the model by looking at another sample within the same organization. This follows H1a stipulating that the circumplex model will be found, by looking at a leader only survey resulting in (H1b) that evidence of the circumplex model in will also be found in leader only qualitative data. There aren't any a priori hypotheses about how the patterns of response might differ between a leader only and a full employee population therefore I

ask the research question (R1) will the same model pattern from one sample of employee

data will emerge in another leader-based sample?

Responses

As qualitative data also has the complication of having nonresponse that is

frequently higher than quantitative data I explored response results to understand

characteristics of qualitative responses in this sample. With these non-responses, it can

follow patterns with employees at higher levels responding at a higher rate (Andrews,

2005). Therefore, I believe the data will replicate here and (R2) there will be a higher

response rate with leaders only compared to a sample of all employees. As management

level has been shown to vary, something such as employee job type could vary. This

could especially be true in more demanding environments with high levels of stress and

interaction with customers, potentially decreasing time and focus on responding leading

to (R3) is there a difference in job type in response rates?

Another aspect that is relevant to explore is differences in employee qualitative

and quantitative sentiment. Employee open-ended responses have been found to typically

match the quantitative responses; however, this hasn't been examined with a high level of

desirability to respond positively leading to the second research question. This might be

especially true when the organization rewards groups for high responses following the

folly of rewarding positives responses (A) while hoping for accurate responses (B). (Kerr,

1975) as is the case in the employee survey used here. Therefore, I ask (R4) is there a

difference in positivity in the qualitative comments compared to favorable survey

responses quantitative data? Answers to these research questions can this analysis

potentially gives us more insights into the clustering results in H1a & b. This is especially important as the use of ML in analysis is relatively novel and in order to have more confidence in any conclusions drawn from this new analysis technique, we have to understand the sample as well as we can.

<u>Testing the Model with Theoretically Related Constructs</u>

As stated earlier, to test models it's also important to see how it connects to theoretically related constructs. When Oreg et al. (2018) proposed the affective circumplex model they indicated individual characteristics that were likely to predict their reactions in the place in the affective circumplex model. I'd like to explore aspects of that as well as some other theoretical constructs that I believe to be correlated to this model further exploring different directions that are frequently researched in organizations.

<u>Goal Alignment</u>

One area that Oreg proposed that predicted reactions in the circumplex model was based on how personal goals relate to reactions. Personal goals can be defined as future-oriented representations of what individuals are striving for in their current life situations and what they seek to attain in various life domains (Brunstein, Dangelmayer, & Schultheiss, 1996). These personal goals are an integral part of individuals everyday life providing direction and drive impacting satisfaction and well-being (Emmons 1996; Maier & Brunstein, 2001). They also are impacted by the organization they are in, when an individual's personal goals or values align with the goals of a new organizational

context, they are more driven toward those goals and have increased wellbeing (Maier &
Brunstein, 2001). As individuals prefer to avoid situations that are unpleasant (Gross,
1998) such as a decrease in wellbeing, they are also likely on the other side of that coin to
support developing an environment that facilitates the achievement of their personal
goals and increased wellbeing. With that we hypothesize (H2a) that congruence of
personal and change related goals will be related to positive and active change reactions.

<div align="center">Burnout</div>

One individual state that can have a large impact on an individual's reaction to change is
burnout. Burnout occurs when someone has "chronic emotional and interpersonal
stressors on the job, and is defined by the three dimensions of exhaustion, cynicism, and
inefficacy" If someone is burnt out they feel less engaged (Maslach, Schaufeli, & Leiter,
2001) and have negative work outcomes for example absenteeism (Yaniv, 1995). When
studying burnout in relation to acceptance of change, factors for burnout such as
exhaustion were significantly negatively related to acceptance of change (Leiter &
Harvie, 1988). Burnout is also related to negative individual states and affect such as less
satisfaction, more stress, and less feelings of control (Rabatin, Williams, Manwell,
Schwartz, Brown, & Linzer, 2016). However, since burnout is conceptualized as
exhaustion and cynicism these negative states might not be as active but due to resources
being devoted to other stressors causing burnout (Nahrgang, Morgeson, Hofmann, 2011).
Taking those factors into consideration, in this model we hypothesize (H2b) that higher
burnout is related to more negative and less active responses.

Declarative Knowledge

Declarative knowledge is "what cognitive psychologists traditionally consider to be knowledge, that is, storage of facts and events" (Ten Berge & Van Hezewijk, 1999, pp. 608). When implementing a new change, there is a certain level of knowledge that can be associated with the different parts of the intervention. As it gets rolled out different individuals in the organization can have different levels of knowledge about new processes and procedures as the change gets communicated (Bloodgood & Salisbury, 2001; Wilcox-King & Zeithaml, 2003). Research has also shown that that communication of knowledge is a critical part of changing systems (Kitson, 2009) As someone is more familiar, they are more likely to have an informed opinion (Bhatti, 2010). Therefore, we hypothesize (H2c) that a higher level of declarative knowledge of the change will be related to increased activity.

Change Participation

One outcome that most organizations would be interested in is how much someone participates in the change. As we've state earlier the affective behavioral circumplex model involves individual's activity related to their reactions and therefore would theoretically related be individuals actually acting around the change. Even though activity is a part of behavioral responses, those that are negative in their active responses are less likely to participate in opportunities to become more informed or practice the change but would be more likely for having their activity show up thorough voice and influencing others (Oreg, 2006; O'Neill & Lenn, 1995). With many interventions having things like voluntary classes on what is involved in the change or information available

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online as a way to participate, as well as processes for using the factors of the change at work we hypothesize (H2d) that individuals who have more positive active reactions are more likely to (A) participate in events related to the change, (B) self-identify as following the procedures of the change

CHAPTER FOUR

METHOD

Overview

Table 4.1 below shows the primary hypotheses (as discussed above) and the data sources/samples associated with each hypothesis. The open-ended data were analyzed using the machine learning approach described above while the quantitative (survey) data and the response rate data were analyzed using traditional statistical approaches.

Table 4.1 Hypotheses and Related Samples

Source & Hypothesis	H1a	H1b	R1	R2	R3	R4	H2a	H2b	H2c	H2d
Employee Open Ended	X		X	X	X	X				
Employee Quantitative				X	X	X				
Leader Open Ended		X	X	X			X	X	X	X
Leader Quantitative				X			X	X	X	X
Participation Data										X

(H1a) evidence of the circumplex model in will be found in the qualitative data.

(H1b) that evidence of the circumplex model in will be found in leader only qualitative data.

(R1) will the same model pattern from one sample of employee data will emerge in another leader-based sample?

(R2) there will be a higher response rate with leaders only compared to a sample of all employees.

(R3) is there a difference of job type in response rates?

(R4) is there a difference in positivity in the qualitative comments compared to favorable survey responses quantitative data?

(H2a) Congruence of personal and change related goals will be related to positive and active change reactions.

(H2b) Higher burnout is related to more negative and less active responses.

(H2c) A higher level of declarative knowledge of the change will be related to increased activity.

(H2d) Individuals who have more positive active reactions are more likely to (A) participate in events related to the change, (B) self-identify as following the procedures of the change

Sample - Quantitative and Open Ended, Employee and Leader

This study is based in a large hospital system of approximately 15,000 employees experiencing an organizational change initiative related to a cultural change of practicing conscious leadership and professionalism. Data for analyses used for H1a, R1, R2, R2, R3, and R4 was pulled from an annual employee survey that asks questions related to the organization including the change efforts. For model testing responses to the question of "Is there anything else you would like to share with the Clemson research team regarding your experiences with Conscious Leadership/Professionalism at GHS?" were

qualitatively analyzed through machine learning. The overall employee survey had 14,249 employees that responded, and 4257 employees answered the open-ended question. Out of that 4257 a little under half (1986; 47%), had responses such as "no" or "n/a" that are similar in meaning to non-response. These were removed for analysis resulting in a total of 2271 qualitative responses from the employee survey used. An additional characteristic of the 2271 responses is that 1601 did not direct their response toward conscious leadership. As this could impact the research and hypotheses directed toward the change initiative analyses were run on the 607 responses related to Conscious Leadership/Professionalism.

Data for analyses used for H1b, R1, and H2a-d were pulled from a separate leadership survey polling about 1000 employees from the same organization that asks questions related to the organizational change. For model testing responses to the question of "Please share any feelings/reactions to Conscious Leadership/Conscious Professionalism" was also qualitatively analyzed through machine learning using BERT (Bidirectional Encoder Representations from Transformers). The leadership survey had 789 employees that responded, and 348 employees answered the open-ended question. Out of that 348 about a fourth (82; 23%), had responses such as "no" or "n/a" that are similar in meaning to non-response. These were removed for analysis resulting in a total of 266 qualitative responses from the leadership survey used. An additional characteristic of the 266 responses is that 27 did not direct their response toward conscious leadership. As this could impact the research and hypotheses directed toward the change initiative analyses were run on the 239 responses related to conscious leadership. To examine

employee event participation a list of number events attended was connected by employee and was able to be connected with 230 of the responses on which the correlations were run.

<div align="center">Machine Learning and Clustering Analysis</div>

To perform the machine learning analysis for H1a, H1b, and R1, the text was mapped in a large numerical vector system through word embeddings. To map these online sources are often used that are pre mapped with the associations in typical human language that are consistent. However, the machine learning process BERT, is also able to context past word embeddings in language overall to also look at the relationships of words within a sentence. This allows the specific word to have different meanings depending on the words that surround it in the sentence. An example of this is the use of the word "bear" in these two sentences "We have the right to bear arms." and "They saw a bear on their hike." Using BERT I was able to differentiate between these two uses of the word. To help with understanding what words mean in human language foundationally BERT is founded in pre trained models that are applied to the current data. I used the Wikipedia and Books corpus which has billions of tokens pulled from text in order to approximate regular English.

For the computing system to learn the text and make inferences, a number of steps were followed. It starts with tokenization, first the open-ended responses were split into words, and pieces of word depending on what it means to result in a better understanding of the word. These tokens were derived from words and parts of words from the Wikipedia and Books corpus. The model then learned numeric embeddings of each token

depending on each other token. From there it formed embeddings based on context representation. Then the full sentence was put together with an average of its tokens.

With data related to specific subject matter however, it can often be relevant to incorporate the new meanings of the words and how they appear together. To factor this in as well as looking at affect and activation outcomes, once the words in the sentence have their own embeddings before it gets factored back into the sentence, the model is trained on the specific context of activation and affect related to conscious leadership. To get to the training dataset responses were coded by two expert coders and inter-rater reliability for the coders was calculated using intraclass correlation (ICC). This coding is set on 1-6 scale of activation and a 1-6 scale of negativity/positivity affect. The determinant of activation and affect was developed through training based on the theory of the literature as well as coming to agreement on a subset of the data for frame of reference training.

To bring in this data the model is trained on 70% of the responses and connected human codes for activation and activity are then tested against a validation set of 10% of the responses. The model was then re-run to fine tune the model to get to its most accurate state. Then to get final accuracy numbers predictions were run against a final test set (20%) of the data and checked for similarity with rater responses using intraclass correlation (ICC). The final predicted numbers for the full dataset are then used to test the rest of the hypotheses.

To test how the data fits into the quadrant model as well as if the model is similar for both data sets testing H1a, H1b, and R1, the activation and affect predicted data were

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used to examine how individuals' responses to the open-ended questions clustered

together. To see if individuals' responses fit the model multiple methods were used. Note

that there are two goals of a clustering analysis: (a) to determine the number of clusters

that best fit the observed data (this is conceptually similar to deciding on the proper

number of factors in a factor analysis); and (b) determining the centroids of the clusters

and interpreting their substantive meaning. To these ends both Two-Step cluster analysis

and traditional k-means cluster analysis were used. The Two-Step method essentially

chooses the optimal number of clusters (and provides an index of goodness-of-fit) but to

bolster this approach, k-means analyses specifying different numbers of clusters were

used as well. This was then compared across samples.
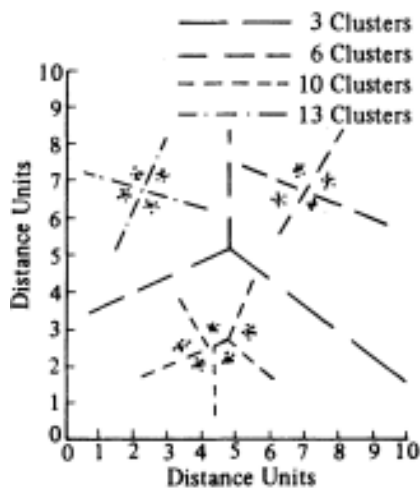

Figure 4.1: Separation into Three, Six, Ten, and Thirteen Clusters

(Divies & Bouldin, 1979; example see Figure 4.1).

<u>Response Analysis</u>

To understand the qualitative response differences in between groups a z-test for

the difference between two independent proportions was conducted. This was used to

compare the qualitative response rates out of everyone that participated in the employee

survey to the qualitative response rates out of everyone that participated in the leadership

survey for R2. For R3 employees have an index of if they spent over or under 50% of

their time taking care of patients directly. Org unit levels of this were then determined by

if the everyone in that unit spent over 50% of their time in patient care, had a mix of

those that did and did not spend over 50% of their time in patient care, or had everyone in

the unit spend less than 50% of their time in patient care. Qualitative response rates were

then looked at comparing number of responses for each of the groups to number of total

participants across both the employee and leader surveys.

To explore R4 as there is only organizational unit information available to

connect the open-ended responses and the full employee survey, I calculated average

scores for employee affectivity and employees' ratings of leaders' level of conscious

leadership. I then took those levels and calculated a correlation between the two variables

at the organizational unit level.

<u>Model Theoretical Testing Analysis</u>

Hypotheses H2a-H2d will all be tested through correlating the affect and

activation scores with the survey response scores (for survey data see Appendix A). H2a

will be tested by using a 4-item measure on a Likert scale of goal congruence or

alignment developed by Supeli & Creed (2014). Those responses will be averaged for

one alignment score, and then correlated to affect and activation derived from responses.

H2b will be tested by using an adjusted Maslach Burnout Inventory (Maslach, et al.,

1986) with 9 items on a Likert scale and three dimensions. This burnout score will then

be averaged and correlated to affect and activation from responses. H2c will be tested

through taking a Declarative Knowledge change content based a 28-question quiz. A

score will then be calculated on a percentage of 1-100%, and then correlated to activation

derived from responses. For H2d (A) Participation, this will be measured using number

of events attended, which will then be correlated to affect and activation reaction scores.

H2d (B) Participation will be tested through a designed scale of individual facilitation of

conscious leadership climate. This has 4 items on a Likert scale which will then be

averaged and correlated to affect and activation responses. To summarize the hypotheses

and related tests they are organized and listed in table 4.2.

Table 4.2 Hypotheses and Associated Statistical Tests

Hypothesis	Test
H1a, H1b, R1	
Machine Learning	
	BERT (Bidirectional Encoder Representations from Transformers)
Reliability & Accuracy	Intraclass Correlation (ICC)
Clustering	Two Step Cluster, Scree Plot, K Means Cluster
R2, R3	Z-test for diff of two independent proportions
R4, H2b-H2d	Correlation

CHAPTER FIVE

RESULTS

<u>Machine Learning Training, Reliability, and Accuracy</u>

To train the data, all labeled data was included from both coders. Additionally, to further train this model, the full dataset is put through multiple times to understand the tokens and word embeddings in a sentence using the pretrained BERT model. To train on the experimental data, 70% of the data was used as training data, and 10% was validation data. The model was run through the training data 20 times each time updating and fine tuning the model to improve accuracy when prediction the validation data. The model was then tested in 20% of the data that it had not seen for final accuracy numbers. The Machine learning model was found to have 2-class accuracy (distinguishing positive and negative) at 85% in comparison to 50% if the data were random for both activation and affect. We are seeing 1-6 accuracy at 50% compared to 16.6% if the data were random. The intra-class correlation (ICC) reliability for raters and the model was calculated for consistency using a two-way mixed model. For interrater reliability, the ICC between both rater 1 and rater 2 for affect was significant ($p<.001$) *and* indicative of good reliability (ICC=.850) with a 95% confidence interval of .837 to .862 (F= 6.677). The ICC between both rater 1 and rater 2 for activation was also significant ($p<.001$) *and* indicative of good reliability (ICC=.805) with a 95% confidence interval of .788 to .820 (F= 5.129, p<.001). A high degree of reliability was found between predicted affect and rater affect measurements as well as predicted activation and rater's activation. The ICC for rater and predicted affect in the employee survey was .905 with a 95% confidence

interval from .898 to .912 (F= 10.529, p<.001). The ICC for rater and predicted activation in the employee survey was .901 with a 95% confidence interval from .894 to .908 (F= 10.130, p<.001). The ICC for rater and predicted sentiment in the leader survey was .799 with a 95% confidence interval from .744 to .842 (F= 4.967, p<.001). The ICC for rater and predicted activation in the leader survey was .795 with a 95% confidence interval from .738 to .839 (F= 4.867, p<.001).

<div align="center">Cluster Formation</div>

To test how the data fits into the quadrant model and test H1a, H1b, and R1, the activation and affect predicted data were used to examine how individuals' responses to the open-ended questions clustered together. Multiple methods were used to understand if individuals' responses fit the model. Note that there are two goals of a clustering analysis: (a) to determine the number of clusters that best fit the observed data (note that this is conceptually similar to deciding on the proper number of factors in a factor analysis); and (b) determining the centroids of the clusters and interpreting their substantive meaning. To these ends, both Two-Step cluster analysis and traditional k-means cluster analysis were used. The Two-Step method essentially chooses the optimal number of clusters (and provides an index of goodness-of-fit) but to bolster this approach, k-means analyses specifying different numbers of clusters were used as well.

To understand how the predicted affect and activation cluster, the predicted responses from the employee survey were plotted (Figure 5.1). the Two-Step cluster analysis resulted in 3 clusters with a good silhouette measure of cohesion and separation above the .5 level. With 3 defined clusters, the k means analysis found (out of a 1-6 range) the

centroids and number of responses per cluster. The cluster 1 centroid had an affect level of 2.44 and activation level of 4.11 with 201 responses in the cluster. The cluster 2 centroid had an affect level of 3.28 and activation level of 1.49 with 236 responses in the cluster. The cluster 3 centroid had an affect level of 4.09 and activation level of 3.99 with 233 responses in the cluster. The result of three clusters fails to find support for H1a.
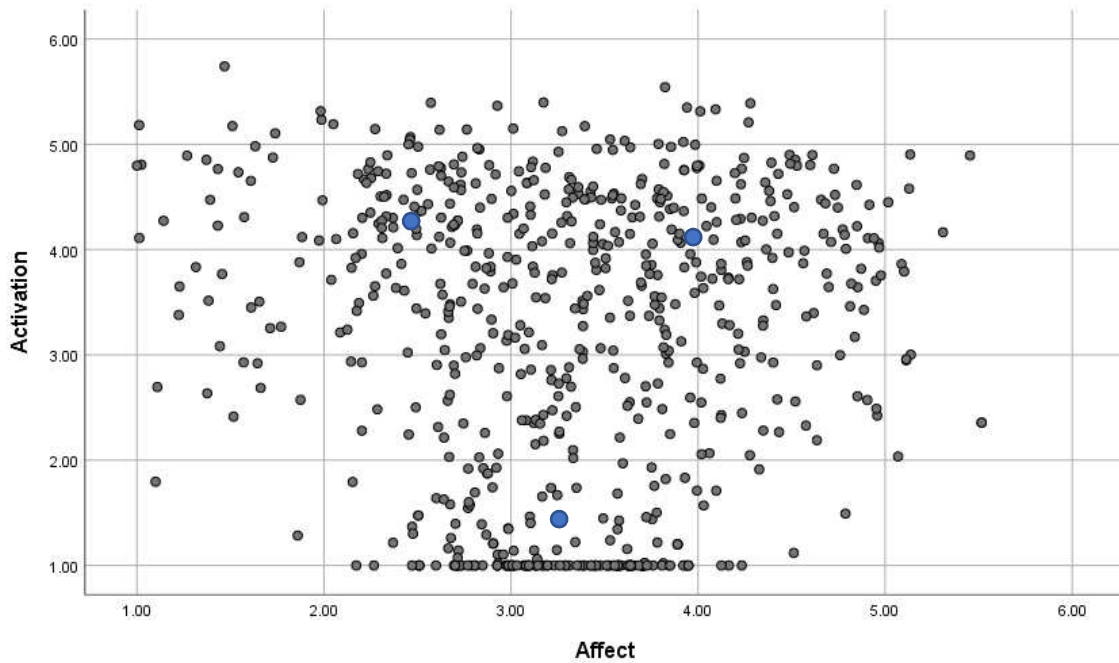
Figure 5.1: Employee Survey Predicted Conscious Leadership Activation and Affect Scores With K-Means Centroids

To understand how the predicted affect and activation cluster in another sample, the predicted responses from the leader survey were plotted (Figure 5.2). the Two-Step cluster analysis resulted in 3 clusters with a good silhouette measure of cohesion and separation above the .5 level. With 3 defined clusters, the k means analysis found cluster 1 centroid had an affect level of 3.66 and activation level of 2.18 with 34 responses in the cluster, the cluster 2 centroid had an affect level of 2.64 and activation level of 4.23 with

82 responses in the cluster, and the cluster 3 centroid had an affect level of 4.13 and activation level of 4.40 with 123 responses in the cluster. The cluster patterns did not find support for H1b. The leader clusters following the same pattern as the clusters for all employees does provide support for H3.
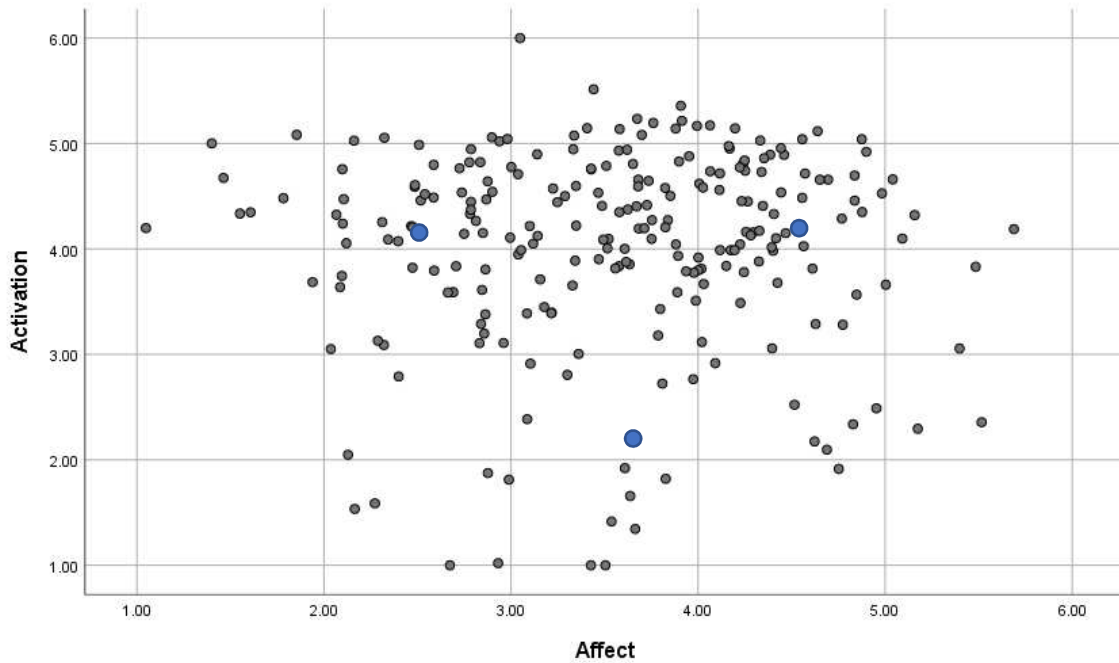

Figure 5.2 Leadre Survey Predicted Conscious Leadership Activation and Affect Scores With K-Means Centroids

Response Characteristics

When looking at the response differences in leaders and all employees the Z test for the difference between two independent proportions indicated that there was a significant difference in qualitative response rate for leaders 34% compared to all employees 16% (z=12.98; $p<.01$). This provides support for R2 that there will be a higher response rate with leaders only compared to a sample of all employees.

When looking at the research question about response differences in unit patient care job type, the z test for the difference between two independent proportions indicated that there was a significant difference in qualitative response rate for the survey for all employees. Less than 50% patient care units (response rate = 10%) were higher compared to more than 50% patient care units (response rate 7%; z = 2.28; $p<.05$). Combined units (response rate = 24%) were higher compared to less than 50% patient care units (z = 22.83; $p<.01$). Combined units were also higher compared to more than 50% patient care units (z = 9.43; $p<.01$). When looking at unit job function with the leader survey the z test for the difference between two independent proportions indicated that there was not a significant difference in qualitative response rate for the survey for all groups. This provides partial support R3 that there will be a difference in response rate based on unit job function.

When looking the relationship of employee affectivity and employees ratings of leader's conscious leadership, results of the Pearson correlation indicated that there was not a significant positive association between employee affectivity and employees ratings

of leader's conscious leadership, (r(314) = -0.1, p = .078). This indicates a lack of support for R3.

<div align="center">Relationships Between Activation, Affect, and Theoretical Constructs</div>

To examine how the predicted activation and affect responses were associated with the theoretically related constructs, Pearson correlations were conducted and are shown in Table (5.1). Results of the Pearson correlation between goal congruence and affect indicated that there was a significant positive relationship (r(239) = .41, p <.001). Results of the Pearson correlation between goal congruence and activity indicated that there was not a significant relationship (r(239) = .121, p = .062). This provides partial support for H2a.

When looking at burnout, results of the Pearson correlation between overall burnout and affect indicated that there was a significant negative relationship (r(239) = -.28, p <.001). Results of the Pearson correlation between overall burnout and activity indicated that there was not a significant relationship (r(239) = -.121, p = .062). Burnout was also split into three subscales emotional exhaustion, depersonalization, and reduced personal accomplishment.

Results of the Pearson correlation between the burnout subscale emotional exhaustion and affect indicated that there was a significant negative relationship (r(239) = -.251, p = .012). Results of the Pearson correlation between emotional exhaustion and activity indicated that there was not a significant relationship (r(239) = .003, p = .967).

Results of the Pearson correlation between the burnout subscale depersonalization and affect indicated that there was a significant negative relationship (r(239) = -.229, p

<.001). Results of the Pearson correlation between depersonalization and activity also indicated that there was a significant negative relationship (r(239)= -.173, p = .007).

Results of the Pearson correlation between the burnout subscale reduced personal accomplishment and affect indicated that there was a not a significant relationship (r(239) = -.106, p = .103). Results of the Pearson correlation between reduced personal accomplishment and activity indicated that there was a significant negative relationship (r(239) = -.193, p = .003). This provides partial support for H2b.

With the association of declarative knowledge and the predicted responses, the results of the Pearson correlation between declarative knowledge and affect indicated that there was not a significant relationship (r(239) = .055, p = .401). Results of the Pearson correlation between reduced declarative knowledge and activity indicated that there was a significant positive relationship (r(239) = .252, p = .003). This finding provides support for H2c.

When looking at participation and predicted scores, results of the Pearson correlation between self-identifying as following the procedures of the change and affect indicated that there was a significant positive relationship (r(239) = .303, *p* < .001). Results of the Pearson correlation between self-identifying as following the procedures of the change and activity indicated that there was a significant positive relationship (r(239) = .152, p = .019). Results of the Pearson correlation between participation in events and affect indicated that there was not a significant relationship (r(230) = -.001, p = .993). Results of the Pearson correlation between participation in events and activity indicated

that there was a significant positive relationship (r(230) = .177, p = .007). This finding

provides partial support for H6.

Table 5.1 Predicted Conscious Leadership Affect and Activation Correlation with

Theoretical Constructs

Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Affect	-									
(2) Activation	0.01	-								
(3) Goal Congruence	0.41**	0.12	-							
(4) Burnout All	-0.28**	-0.12	0.36**	-						
(5) Emotional Exhaustion	-0.35**	0.003	0.24**	0.90**	-					
(6) Depersonalization	-0.22**	-0.17**	0.21**	0.79**	0.62**	-				
(7) Reduced Personal Accomplishment	-0.10	0.19**	-0.20**	0.55**	0.22**	0.21**	-			
(8) Declarative Knowledge	0.06	0.25**	0.55**	0.31**	0.26**	0.19**	-0.12**	-		
(9) Climate of Participation	0.30**	0.15*	0.65**	0.38**	0.27**	0.19**	0.21**	0.43**	-	
(10) Event Participation	0.18**	-0.001								-

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

CHAPTER SIX

DISCUSSION

<u>Machine Learning and Clustering</u>

Through the machine learning based scores and the cluster analysis, we did not find evidence of four clusters or support for the four-quadrant model. Thus, there was a lack of support for H1a and H1b. From the cluster analysis, it looks as if a three-cluster model more accurately describes the data. Specifically, the three clusters are: high activation and negative sentiment, high activation and positive sentiment, and low activation and neutral sentiment. This configuration was found for all employees and also found for leaders who gave responses related to conscious leadership. What this could indicate is that people are more likely to respond more actively with higher levels of positivity or negativity whereas those in the middle are more likely to respond less actively. This indicates that affect is important and can drive activation.

The modeling through machine learning did, however, appear to be reliable and generalizable with the clusters appearing in both datasets, supporting R1. Since the clusters looked similar across groups, this indicates that samples would have similar configurations of responses to a change initiative even with slightly different groups and questions. Additionally, the machine learning process activation and affect ratings were found to have a high ICC, with raters and across the training and test sets, which means that the model was able to consistently learn responses and provide accurate ratings. This supports that training a machine learning model (BERT) on a theoretical concept can result in an ability to predict the level of that concept in an open-ended response.

<center>Response Patterns</center>

Looking at response rates, R2 was supported, stating that leaders will respond to open ended questions at a significantly higher rate than overall employees. As their jobs could quite possibly involve a frequent amount of feedback due to leading a team and making decisions, therefore this experience may make responding to an open-ended question could come more naturally.

When it comes to if response rates are different for unit patient care responsibility variation, being in a combined unit (mix of those that are in direct patient care over 50% of the time and those that are in patient care less than 50% of the time) had the highest rate of responses. This could be because there is more variability or working together in their team to care for patients and more need for feedback; therefore, they were more likely to respond. Following the combined group, units with only those that spend less than 50% of the time in patient care responded the next highest rate. This could be due to having job types where they might have to interact interpersonally with other coworkers more frequently and use the survey as the outlet or simply have more computer time to fill out the survey. Units with only those that spend more than 50% of their time in patient care responded at the lowest rate, which is understandable if they spend more time with patients and potentially had less time to complete the survey.

These results of organizational unit differences did not, however, hold true for the leader population, as there were no significant differences. This could be due to more similarities in leader job characteristics These findings show partial support for R3 that there is a difference between patient care org unit variation with it being only shown in

one sample. This indicates that job type can make a difference in response rates and should be taken into account when analyzing data although if participants in a sample have jobs that function similarly overall (e.g. leaders) that could mitigate this.

Exploring the relationship between employee affectivity and employees' ratings of leader's conscious leadership found no significant correlation not supporting R4. This is interesting, as typically, ratings are similar with no incentive. However, these measures are not entirely the same, which may have an impact on this finding. There is also the consideration of incentives where this employee survey is connected to positive organizational consequences with high scores so that also could have resulted in putting higher scores and reducing the correlation. Given this finding researchers and employers alike should be careful of how placing incentives with surveys can impact results.

<u>Affect and Activation with Theoretically Related Constructs</u>

Examination of how reactions of activation and affect are connected to theoretically related concepts indicated that most of the content-specific hypotheses were at least partially supported. When looking at the relationship of personal and change related goal congruence with positive and active change reactions, H2a was partially supported. There was a significant relationship with positive affect, but no significant relationship with activation. With the support for positive responses having a significant positive relationship with employees having personal goals that are similar to the goals of the change, this could be caused by liking the change as your goals agree with it but potentially not taken action. This positivity related to goal congruence follows along with

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the concept that employees in organizations that have goals like personal goals increases wellbeing (Maier & Brunstein, 2001).

When examining burnout in relation to activation and affect, H2b was also partially supported. Burnout, all scales, were found to be negatively related to affect, which aligns with the literature that it is associated with negative individual states (e.g. less satisfaction, more stress, and less feelings of control; Rabatin et al., 2016). This also means that burnt out individuals do not look at the change in a positive light, which follows along with Leiter and Harvie's (1988) research that found factors for burnout such as exhaustion were significantly negatively related to acceptance of change. Burnout however wasn't related to activation except for reduced personal accomplishment, which could indicate that resources being devoted to other stressors causing burnout doesn't impact the activity of responses (Nahrgang, Morgeson, Hofmann, 2011). Reduced personal accomplishment could be the only significant negative relationship due to its direct connection to activity which does partially support burnout's negative relationship to activation.

When it comes to looking at declarative knowledge, employee activity was positively related supporting H2c. This follows along with the literature that as someone is more familiar, they are more likely to have an informed opinion (Bhatti, 2010). This also indicates that beyond having an opinion they are more likely to be more active about the subject matter. Additionally, there was not a relationship between affect and declarative knowledge indicating that these opinions can sway either positively or negatively.

Following along with the affective behavioral circumplex involving activity as the behavioral aspect, this was partially supported (H2d, A) with there being some support for activity being related to event attendance although there was no relation to sentiment. This could be due to the increase in event attendance being related to only increased declarative knowledge and acting on beliefs and opinions formed from that declarative knowledge base in either direction (positive or negative). Therefore, this would be a great area for further exploration. As for self-identification, as following procedures of the change (H2d, B), was related to affectivity and activation and therefore supported. This makes sense as they are self-identifying that they participate in and follow along with the concepts. Also, as they are actively participating, they have a positive perspective as the outcome of active negativity is counter to following along with the principles of the change.

Even though analyses didn't support the full circumplx it did support an underlying model that was evident in multiple samples. These three clusters of the model with two points at high activation and affect (negative and positive) as well as one point that was very neutral in affect and low in activation could indicate that affect can partially drive activation. Activation is still important to examine however, as the theoretical hypotheses clearly indicated a difference in activation and affect that follows expected directions. These findings indicate a need to reevaluate the circumplx model to look to see if that's not actually the way employees react to change i.e., there isn't a lot of strong affect connected with low activation (change disengagement, change acceptance).

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There are a few limitations of this study, one of which is that there were a lot of individuals that did not respond, and when they did many of them did not refer to Conscious Leadership. This was especially evident in the employee survey, as there was not another open-ended opportunity for employees to use their voice regarding other issues, so they took that box as an opportunity to do so. This is also notable as there were a lot less unrelated to conscious leadership responses in the leader survey, which had an additional open-ended question for additional comments.

Another limitation was that the employee survey open ended responses could not be directly to the quantitative survey responses at the individual level. This indicates that some of the response rate results and the connection between leader conscious leadership could be impacted through differing variations within unit impacting scores. This also limited additional analyses like were conducted in the leader survey.

With reference to the machine learning aspect of the study, one limitation is that human bias is still incorporated into the model, as the training corpus from Wikipedia and literature has baked into it natural human bias that comes out in language. An additional area where human bias comes into play is with the raters coding of the responses. Although the ratings were reliable and coding was done without access to each other's codes, they were trained together. Even with that, the activation and affect predictions were based on human judgments that the machine learning model was trained on. Additionally, since the machine learning model is trained on specific contexts for affect and activation (in this case conscious leadership), it is a limitation that to use this for

another organization or subject the model would need to be retrained on a fairly large dataset (>1000). However, once it is then it is able to be applied even with slightly different samples and question formats.

Another area that can be a slight limitation is that specifications of machine learning models can be difficult and slight tweaks can change response information. With that said, it is vital to be cautious with how the model is being assembled and to ensure checking for accuracy.

Clustering is another area that is difficult to work with and has its limitations. K-means for example cannot determine number of clusters but can only describe them. Additionally, the true number of clusters can be tested, but it also takes some subjectivity to examine the plots to see if the numbers are following the patterns seen by researchers and not influenced by potential aspects of the data.

Future Research

From this study, it would be of great value to use this machine learning process on other organizations. This would help validate the cluster shapes to see if it is something that is not organization specific. Another area that would be beneficial for future research is looking at the clusters and machine learning analysis of responses over time. This could be an excellent way to study an organization's journey as it goes through change. The BERT model can also be used to get more in depth with additional theoretically related outcomes especially those related to organizational success (e.g. monetary outcomes). Along with that more complex experimental design can be used to explore causation of the varying theoretical associations. This also poses the idea to train and use

BERT to examine other theories. This could be applicable to countless different organizational theoretical characteristics overall.

Application

One major area that using machine learning in open ended questions provides a great advantage is that organizations can use this fast in surveys over time. This makes open ended responses more usable to take actions when needed. This also can allow the context of employee feedback information to be used instantly. If an organization is going to use this method to collect data about a specific subject it is however recommended that they include an open-ended question that says "what else?" Another great application of this study is that if an organization is being able to look at and monitor positivity and affectivity throughout rollout and know that as people learn more, they are likely to be more active. Along with that having positive views are related to beneficial outcomes. Therefore, if one area of the organization is low in activation and more negative it could be time to devote additional support to that group.

Summary

Although the circumplex wasn't supported, there were interesting generalizable results about employee affect and activation related to an organizational change namely that more negative or positive were more active and that neutral responses are typically less active. When looking at affect and activation, they were also related to some key individual information surrounding an employee's experience and state. Lastly, the

machine learning method to get to these results was also found to be an extremely useful

method for understanding qualitative data.

Survey Questions

Adjusted Maslach Burnout Inventory

1. I deal very effectively with the problems of my patients or customers

2. I feel I treat some patients or customers as if they were impersonal objects

3. I feel emotionally drained from my work.

4. I feel tired when I get up in the morning and have to face another day on the job.

5. I have become more callous toward people since I took this job.

6. I feel I'm positively influencing other people's lives though my work.

7. Working with people all day is really a strain for me.

8. I don't really care what happens to some patients or customers.

9. I feel exhilarated after working closely with my patients.

Scale: 7 pt Likert type scale; (1) Never, (2) A few times a year or less, (3) Once a month or less, (4) A few times a month, (5) Once a week, (6) A few times a week, (7) Every day

Goal Congruence

1. My personal goals and values are aligned with the principles of conscious leadership

2. I can attain my personal goals by following the principles of conscious leadership

3. My work-related goals and values are aligned with the principles of conscious leadership.

4. I can attain my work-related goals by following the principles of conscious leadership

Scale: 1-6 strongly disagree to strongly agree

Conscious Leadership Climate Facilitation

1. I share the ideas of Conscious Leadership/Conscious Professionalism with my team.

2. I demonstrate curiosity over defensiveness with my team.

3. I demonstrate seeking to learn over seeking to be right with my team.

4. I demonstrate taking responsibility over blaming and/or complaining with my team.

Scale: 1-5 agreement

Declarative Knowledge: Questions are multiple choice. 28 questions

Scale: Percent Correct out of 100%

<div align="center">**References**</div>

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