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THE MODERATING EFFECT OF MEDIA NATURALNESS ON MOTIVATING LANGUAGE

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ON MOTIVATING LANGUAGE

A Dissertation

by

JAMES COX

Submitted to Texas A&M International University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

May 2019

Concentration: Management Information Systems

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Approved as to style and content by:

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ABSTRACT

The Moderating Effect of Media Naturalness on Motivating Language (May 2019)

James Cox, BBA, MS-IS, Texas A&M International University;

Chair of Committee: Dr. Ned Kock

For decades, the research in communication in organizational behavior has focused on the reduction of uncertainty and consequently so has the research of leadership and computer mediated communication (CMC) (Salancik & Pfeffer, 1977; Sullivan, 1988). Because of this, many of the controversial issues and competing theories of CMC that have in good part centered around the topic of media choice in the context of task performance, which is a reflection of this narrow focus of CMC on uncertainty reduction. Therefore in order to study the more whole form of communication in motivation proposed by Sullivan (1988), a CMC theory is needed that is not constrained by this narrow focus of media choice as a function of uncertainty reduction.

This paper attempts to fill this need by proposing a measurement scale for the media naturalness theory proposed by Kock (2004), which is validated through personal interviews in a manner similar to those conducted by Russ, Daft, and Lengel (1990) and Trevino (1990). A research model and hypotheses were developed based on literature in order to analyze the predicted moderating effect of media naturalness on motivating language. In order to strengthen the study, several confirmatory relationships whose expected path coefficients are well documented in the literature are examined and the research was conducted in a pilot study and main study using WarpPLS to implement PLS-SEM. The Main study has a sample of 351 respondents gathered through Amazon Mechanical Turk: 196 from the US and 165 from India.

Although the moderating effect was only supported in the pilot study, a detailed analysis of the results as well as structural and measurement models revealed that the confirmatory relationships were consistent with the literature in the pilot and main studies. It also reveals that the proposed measurement scale for media naturalness has cross-cultural validity in the US and India, as well as those for motivating language, job satisfaction, organizational commitment and job performance. A multigroup analysis shows that there was no measurable difference between the two subsamples. An exhaustive discussion of the results, implications, limitations, future research and practical applications is also presented.

DEDICATION

This dissertation is dedicated to my wonderful wife, Milena. It was you who encouraged me to enter the doctoral program. It was your unique insight that allowed you to know before I knew myself how I would find in the pursuit of life in academia a source of joy and fulfillment. Thank you for being yourslef. Thank you for being my better half.

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CHAPTER I

INTRODUCTION

Computer mediated communications (CMC) is a topic that many studies on communications have researched and discussed. Thus, this literature has generated many controversial issues and competing theories that are in good part centered around the topic of media choice in the context of task performance. But, in the words of Schmitz and Fulk (1991), these "research strategies more often focus on technical advantages and task requirements to 'explain' the adoption and use of new media" (pp. 487-488).

One of the earliest and most widely cited of such theories is media richness theory (MRT). It conceptualizes the organization as an information processing system where managers are constantly processing information in order to learn and make decisions. When they need new information but it is not readily available, they seek it; and in doing so, they choose the communication medium that will best help them reduce the equivocality of said information (Daft & Lengel, 1984; Lengel & Daft, 1984). When the information has a complex and highly equivocal nature, managers will use a richer medium such as face-to-face communication, and when it is less equivocal, they will use a leaner form of communication (Daft, Lengel, & Trevino, 1987). Daft and Wiginton (1979) have addressed the idea of using natural language to communicate certain complex phenomena and it has been a topic of interest in the area of information channel use in the research on the sharing of scientific information (Bodensteiner, 1970).

Initial studies found support for MRT but they were somewhat problematic since they used hypothetical scenarios of media choice (Russ, Daft, & Lengel, 1990), media ranking

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This thesis follows the model of *MIS Quarterly.*

scenarios (Trevino, 1990), or asking executives to recall individual instances of media use and choice (Daft et al., 1987). Schmitz and Fulk (1991) initially attempt to address these problems by conducting empirical research. They find that managers perceive email as a lean medium as predicted by MRT. However, later studies did not support these findings. Rice and Love (1987) find that users are capable of transmitting moderate socioemotional content via email. Additionally, Fulk and Ryu (1990) fail to obtain media rankings that coincide with MRT's media richness rankings after interviewing executives, and Markus (1990) finds instances of executives utilizing email for tasks with high degrees of ambiguity, which is contrary to MRT's predictions on media use.

Channel expansion theory (CET) was proposed by Carlson and Zmud (1994) in an effort to reconcile these seemingly contradictory and problematic findings that emerged in the field of MRT research. To achieve this goal, the authors introduce elements of situational factor theory (Trevino, Lengel, & Daft, 1987) as well as social presence theory (Short, Williams, & Christie, 1976) in their study of email communications. They thus postulate that although the medium's richness is a defining factor in media choice, a person's previous experiences with the medium, topic, organizational context, and the communication partner affect their perceived richness of the communication medium (Carlson & Zmud, 1994, 1999).

In their study D'Urso and Rains (2008) expand CET research by adding telephone and instant messaging to the traditional face-to-face versus email postulation of CET and find empirical support for the theory. A more recent longitudinal study of online discussion forums finds that variations over time in the perceptions of the richness of the communication channel are due to changes in acquired experiences, which supports CET's premise that learning experience leads to a perceived increase in the richness of the communication channel

(Fernandez, Simo, Sallan, & Enache, 2013).

However, CET has some important concerns that remain unresolved. The first concern is whether a channel's inherent technological features restrict its ability to "expand" (Timmerman & Madhavapeddi, 2008). The second is the seemingly paradoxical occurrence of the voluntary initial adoption of email instead of face-to-face communications, even when it is considered a leaner medium (Kock, 1998) and performing as good as or better than face-to-face communications, although the theory ranks email as leaner and thus less adequate (Kock, 2005a).

Much like CET, media synchronicity theory (MST) was introduced to address the seemingly contradictory empirical findings in MRT research (Dennis & Valacich, 1999). At the core of the theory is the concept of media synchronicity that the authors define as "the extent to which a communication environment encourages individuals to work together on the same activity, with the same information, at the same time; i.e. to have a shared focus." (Dennis & Valacich, 1999, p. 2). Unlike CET, the authors identify MRT's principal shortcoming as the attempt to match a communication channel to a task. In order to address this shortcoming, the authors specify that communication channels have one or more different physical capabilities. They argue that these physical capabilities should be matched to the task (Dennis & Valacich, 1999).

The first of these capabilities is transmission velocity that represents the speed at which the medium can transmit the information. Second is parallelism that reflects the extent to which the medium can transmit the signals from multiple senders in a simultaneously. Third is symbol sets that represent the different ways in which the medium can encode information. Fourth is Rehearsability, which is the ability to rehearse and recompose the encoding of the message before transmitting the information. Fifth is Reprocessability, which is the extent to which a message can be reexamined (Dennis, Fuller, & Valacich, 2008).

This shortcoming is further addressed in the newest iteration of MST by redefining a task as "*the set of communication processes* needed to generate shared understanding" (Dennis et al., 2008, p. 576) (emphasis in the original). Thus, this new definition now adds two fundamental communication processes to the traditional view of a task: conveyance and convergence. Each of these two processes requires the transmission and processing of information, albeit in a different manner. Thus, this iteration of MST now considers these two communication processes as the task that should be matched to the physical capabilities of the medium. (Dennis et al., 2008) define conveyance as the transmission of new information and state the purpose of convergence is for the people involved in the process come to an understanding on the meaning of the information. In this manner while the original postulation of matching media characteristics to tasks remains unchanged, the fundamental understanding of the theory has changed.

The authors have thus address MRT's shortcomings by postulating a theory of media fit rather than predicting the use of the communication media and by doing so make the concepts of media and task more granular (Niinimaki, Piri, Lassenius, & Paasivaara, 2010), while steering clear of assigning socially-derived characteristics to communication media (Dennis et al., 2008) in the manner of CET (Carlson & Zmud, 1999). In the words of Niimaki: "Media synchronicity theory suggests that effective media use requires a match between media capabilities and fundamental communication processes needed to perform the task." (Niinimaki et al., 2010, p. 4). Thus, the socially derived characteristics of media that defined CET (which can be arguably be said to be a weakness) are not born here by the communication medium, but rather by the construct of media synchronicity.

DeLuca and Valacich (2005) conducted two independent studies on two organizations using action research to study virtual groups in process redesign: organization A with 35 members, and organization B with 41 members. The measure of communication success was the total or partial implementation of the redesigned process within a time frame of six months. The authors also created a measurement instrument that enabled the members to report their media mix use during the study by responding to questions using a Likert-type scale. Open-ended questions were used to gain insight into the results of the reported media mix use. They report that the feedback from these groups regarding the choice of media use lends support to MST. Two of the teams, which were unsuccessful in the implementation of the redesigned process were the ones that reported media use that was not in accordance with MST.

DeLuca and Valacich (2005) find support for MST when studying a set of 12 distributed software teams (DST). The authors collected the data using semi-structured open-ended questions from 79 interviews with two stages of codification done by different researchers. The study finds evidence that supports the applicability of MST in the selection of communication media for global software development (GSD), but the findings can also support media naturalness theory (MNT) (Niinimaki et al., 2010).

A theoretical underpinning of MRT is the conceptualization of an organization as an information processing entity (Daft et al., 1987) whose manifestation in MRT and MRT-derived theories such as CET and MST is a focus on communication equivocality. Is the communication channel appropriate to transfer the information needed to complete the task successfully? It is this underlying conceptualization of an organization as an information processing entity that shackles the study of CMC with an implicitly narrow view of organizational communication: a view that as we will see in a later section, was prevalent in the decades leading to the emergence of MRT. This narrow view could be especially problematic for research in areas such as motivating language theory (MLT) whose central premise is orthogonal to the implicit assumptions of MRT: communication is much more than the transmission of instructions and knowledge.

Although more refined and developed than MRT and CET, MST also shares this implicit constraint, which is articulated by some of its boundary conditions and fundamental assumptions. For example, MST is based on Habermas' ideal speech in which participants should agree or disagree "only from the force of the better argument and no other force" (Habermas, 1990, p. 104). Related to ideal speech is the concept of convergence whose objective is "to agree on the meaning of the information, which requires individuals to reach a common understanding *and* to mutually agree that they have achieved this understanding (or to agree that it is not possible)" (Dennis et al., 2008, p. 580). For certain studies a narrow perspective of organizational communication can be advantageous, such as for the study of virtual teams (DeLuca & Valacich, 2005) and DST (Niinimaki et al., 2010), where successful performance of a defined task within a specified time frame is the metric of communication performance. But as this paper argues that what is an advantage for some types of studies may be a disadvantage for other types that need a broader perspective of organizational communication, such as studying motivating language theory (MLT).

The study of the language of motivation has for decades focused on the reduction of communication uncertainty: If an employee has clear communication regarding a task, its rewards and expectations, the employee will be more motivated and hence more productive. Sullivan notes, perhaps bitingly: "Apparently, workers seek knowledge to reduce uncertainty, and they perform better if they are informed by supervisors" (Sullivan, 1988, p. 105).

This approach of reducing uncertainty reduction to motivate employees was initially the result of the need-satisfaction paradigm that was prevalent in many theories in the fields of Psychology and Organizational Behavior for decades (Salancik & Pfeffer, 1977, 1978; Sullivan, 1988), of which perhaps the most famous is Maslow's Hierarchy of Needs (Maslow, 1943). Although other need theorists debated how these needs should be classified (Alderfer, 1972; McClelland, 1961; Murray, 1938), the common thread is the satisfaction of clearly identified employee needs. Other refinements of this paradigm are the attempt to match self-esteem to a task (Korman, 1976), and matching the need for growth to job characteristics (J. Richard Hackman & Oldham, 1980). Salancik and Pfeffer state: "The literature on job attitudes and task design has been dominated by the need-satisfaction paradigm, a model which asserts that people have needs, jobs have characteristics, and job attitudes (and motivation, in some versions) result from their conjunction." (Salancik & Pfeffer, 1978, p. 224). Although the authors note that there was a debate regarding the adequacy of this approach in Psychology at the time, it had not reached the field of Organizational Behavior (Salancik & Pfeffer, 1978).

Sullivan also notes that the literature on choice theories at the time implied that workers needed to develop knowledge of specific and difficult goals to perform better and that expectancy theory and operant conditioning focus on information is due to the need to reduce reward uncertainty. However, according to equity theory, an employee's demand for information derives from his or her need to ensure fairness (Sullivan, 1988).

This focus on research in organizational communication and motivation provides the context for the emergence of the MRT: The purpose of communication from the organization to the employee according to multiple disciplines was that of clarification and reduction of ambiguity. Sullivan states that according to this need-deficiencies model, "Information (defined as message content that reduces uncertainty) is believed to be crucial in the motivation process. Arousal theories of motivation focus on need-deficiencies in workers and the information that managers supply to the worker to reduce uncertainty regarding the correction of the deficiencies or imbalances.” (Sullivan, 1988, p. 104).

Research Question

It is when this context is taken into account, that the implicit limitations of a view of the organization as an information processing entity and the consequent focus on the reduction of equivocality in the transmission of information as the central tenets of MRT (Daft & Lengel, 1984) come into sharp focus. This study argues that the CMC theories that attempt to improve or refine MRT such as CET and MST, have these similar implicit limitations. As a result, the main perspective of MRT, CET and MST is essentially that communication media choice is a function of the reduction of equivocality or uncertainty (Carlson & Zmud, 1994, 1999; Daft & Lengel, 1986; Daft & Weick, 1984; Dennis et al., 2008; Dennis & Valacich, 1999). This was, after all, a central theme in various social science fields in the decades prior to the development of modern electronic communications and MRT.

Sullivan’s proposal of MLT broadened the scope of study in the field of motivational language to include aspects of communication other than the reduction of equivocality that was the focus of previous theories, it is indeed a recent development. Especially when we take into account the publication of the theory (Sullivan, 1988), scale development (J. Mayfield, Mayfield, & Kopf, 1995), and the establishment of a stream of empirical research as we will see in later sections of this study.

This study proposes that a theoretical perspective of CMC that is different from MRT and its related theories such as CET, and MST is needed to properly conduct research in areas of

Organizational Behavior and Organizational Communications where the underlying assumption of communication as the unequivocal transfer of information and knowledge may prove unduly restrictive, such as motivation, and specifically MLT (J. Mayfield et al., 1995).

This study further proposes that a media naturalness theory (MNT) (Kock, 2004) perspective of CMC addresses several of the shortcomings given in the theoretical background. Although some of the concepts of media richness and media naturalness may appear similar at first glance, the underlying theories and concepts truly sets MNT apart (Kock, 2005b). One of MNT's most salient distinctions, for the purpose of this study, is that it sets an objective baseline for human communication: face-to-face communication is the most natural form of communication, and due to our evolutionary past and history any form of communication that departs from it is less natural, and therefore requires additional cognitive effort, adaptation, or some combination of both. The theory around the evolution of the human communication apparatus and makes evolutionary arguments as to why different aspects of face-to-face communication are important. Thus, the study analyzes media characteristics to determine how they support these evolution-developed communication traits (Kock, 2004). Finally, since MNT is a theory of media naturalness (as its name implies), it does not make predictions or assumptions of media fit, media choice, communication efficacy, or task outcomes (Kock & Garza, 2013). Coincidentally, not only was such a focus on face-to-face and oral communication also central in the initial postulation of motivating language theory (Sullivan, 1988), but it remains so to this date (J. Mayfield & Mayfield, 2018).

The issue of researching CMC in the context of MLT is further complicated by fact that there are multiple CMC platforms that seem to have an ever-changing array of features; the trend in chat platforms to now provide voice, video, and file sharing has been going on for at least the last decade (Dennis et al., 2008). Fast-forward to today: CMC platforms now offer multiple options. The blending of options that start blurring the lines between different communication channels is now taking a different direction: the blurring of lines between communication platform and application. Many applications now include built-in chat, file sharing application sharing features as well as being able to plug in external applications to expand the features of a service platform. One example of such a trend is to use task management systems with integrated chat features that can assign tasks within a chat and can provide external information and content when necessary (Gerber, 2017; Rauv, 2017). This question is especially relevant given the trend to use these various platforms in different forms of communication within the organization (Dennis et al., 2008).

Although some research exists in the field of CMC regarding MLT, it limits its focus to text-based communications in virtual teams in an experimental setting (Wang, Hsieh, Kai-Tang, & Menefee, 2009). To date, no other study has empirically studied how CMC may possibly affect motivating language (ML) across a wide variety of different communication media like in a real-world scenario.

This study attempts to fill this gap in the literature of CMC and MLT by including the relationships between variables that studies have previously addressed and supported in the field of MLT as well as variables and relationships that have not been addressed in the context of MLT. This study also examines the existence of a moderating effect of CMC on motivating language through the lens of MNT.

The study assumes that communication regarding a particular topic will happen in a communication stream and is likely to occur over a mix of communication channels over time, and not necessarily face-to-face. For this purpose, the study proposes and develops a media naturalness scale (MNS) to measure the degree of naturalness (DoN) of each individual communication medium. The weighted mix of communication media is then used to calculate a communication naturalness score (CNS) for each communication stream.

Significance of the Study

The study of the possible moderating effect of media naturalness on the effect that motivating language has on organizational outcomes is relevant for various reasons. First, it will help supervisors understand how the degree of naturalness of their communication ultimately affects the impact that motivating language has on job satisfaction, organizational commitment, and job performance. Second, I examine the relationship between motivating language and organizational outcomes through the lens of MNT in a multi-country study to enrich the scholarly literature on the fields of both MLT and MNT, organizational communications, and CMC. Third, this study helps to establish the validity of the MNS and the CNS by applying it to empirical research in the context of both supported and not yet explored relationships in the field of MLT.

Purpose of the Study

There are several purposes to this study. The first is to develop the MNS to provide scholars in various business and organizational behavior fields a measurement instrument to analyze CMC that is free of the inherent restrictions and assumptions mentioned in the theoretical background. The second purpose of the study is to utilize the MNS in an empirical study and thus attempt to establish its validity. The third purpose of the study is to study the moderating effect of media naturalness on motivating language in an empirical study.

Specifically, the study analyzes whether a supervisor's communication naturalness moderates the effect that motivating language has on organizational outcomes as measured by organizational commitment, job satisfaction, and thus indirectly on job performance. The study is conducted in two culturally distinct countries (the United States and India). The participants are surveyed about the motivating language that they receive from their supervisor: namely, its frequency and what mix of communication media their supervisor uses. They answer questions regarding their organizational commitment, job satisfaction, and job performance. I have purposefully designed the study so that some of the relationships have already been studied and can serve as further validation of this study, as well as including previously untested relationships.

CHAPTER II

LITERATURE REVIEW

Job Satisfaction, Organizational Commitment and Job Performance

A lack of agreement exists on what defines job satisfaction (Lim, 2008), although the field of motivating language has widely studied the concept (J. Mayfield & Mayfield, 2018). A common thread in the literature is that it is an appraisal of job activities that results in a positive or pleasurable emotional state (Moqbel, 2012) and affective reactions to one's job (J Richard Hackman & Oldham, 1975), although different approaches have been taken, such as referring to it as an evaluative process consisting of objects (H. M. Weiss, 2002).

The job descriptive index (JDI) (Kinicki, McKee-Ryan, Schriesheim, & Carson, 2002; Smith, Kendall, & Hulin, 1969), the Minnesota satisfaction questionnaire (D. J. Weiss, Dawis, & England, 1967), and the job satisfaction survey (Spector, 1985) are among the many instruments used to measure job satisfaction. Usually the results vary according to the scale that is used in the study (Moqbel, 2012). While some studies focus on a specific dimension of job satisfaction, such as pay, promotion, or supervision (Porter, Steers, Mowday, & Boulian, 1974), others add other dimensions, such as peers and coworkers (J Richard Hackman & Oldham, 1975). However, Scarpello and Campbell (1983) suggest the use of more inclusive measures of job satisfaction, such as the work by Rehman and Waheed (Rehman & Waheed, 2011) that was used by Moqbel in the study on the use of social networking sites (Moqbel, 2012).

Although there is an unsettled debate regarding the relationship between job satisfaction and job performance, the idea that higher morale leads to higher productivity (Strauss, 1968) has been prevalent for quite some time. The recent research also supports the view that job satisfaction leads to higher performance (Rehman & Waheed, 2011; Zhang & Zheng, 2009).

Organizational commitment is a trait in employees that is highly sought after by firms. At "the very least, high Organizational Commitment leads to lower turnover, and at the best, it leads to extra effort and peak performance from firm members" (J. Mayfield & Mayfield, 2018, p. 82). Organizational commitment has been categorized into three types: *affective, continuance,* and *normative.* Employees that have a strong affective commitment to the organization have an emotional attachment to it and remain employed at it because they wish to do so. Those with a strong normative commitment remain because they feel that they should stay, while those with a strong continuance commitment remain at the organization because they need to remain (Allen & Meyer, 1990). Affective commitment is related to a person's identification and involvement with an organization (Porter et al., 1974) as well as to increased effort at work (Riketta, 2002). Therefore, as in Moqbel (2012) study of social network site use, this study adopts the affective commitment type as its perspective, and it will be from now on referred to as *organizational commitment.*

Job performance has been a subject of interest for decades to organizational researchers (Moqbel, 2012) who have referred to it as the "behavior or actions that are relevant to the goals of the organization in question" (McCloy, Campbell, & Cudeck, 1994, p. 493). Lawler and Porter report that satisfaction of higher order needs is closely related to performance (Lawler & Porter, 1967), and newer studies find evidence that job satisfaction affects job performance (Zhang & Zheng, 2009). Although studies do not agree on the nature of this causal relation, they have found the average correlation to be an estimated value of 0.30 (Judge, Thoresen, Bono, & Patton, 2001).

Motivating Language

The purpose of motivating language can manifest in different ways at different levels of abstraction. At its most abstract, it helps leaders connect with their followers while improving the well-bring of the followers as well as the organization (J. Mayfield & Mayfield, 2018). At a more operational and less abstract level, it uses verbal communication to help align the leader's intent with employee outcomes (J. Mayfield & Mayfield, 2012). Talk is a vital component, since for most leaders, it can account for 60%-80% of their time (Holmes, 2012; J. Mayfield & Mayfield, 2018).

MLT was originally conceptualized and proposed as *motivational language* by professor Jeremiah Sullivan "as a communicative path to enhance follower motivation and related outcomes through mindful and strategic leader speech" (J. Mayfield & Mayfield, 2018, p. 8). He proposed a linguistics-based framework. Mayfield and Mayfield state: "Sullivan asserted that more extensive and strategic language choices by leaders will be perceived as helpful, then in turn nurture higher motivation and desirable follower attitudes and behaviors, such as performance, job satisfaction, and organizational commitment" (J. Mayfield & Mayfield, 2018, p. 11).

Background of Motivating Language Theory

Sullivan's theory was indeed groundbreaking considering the literature that was reviewed in the introduction of this study regarding the past focus of research in the fields of organizational communication and the similar research in the field of leadership. The seminal Michigan and Ohio State leadership studies (from the latter part of the 1950s and 1960s respectively) focused on task-related orientation and people-related orientation (J. Mayfield & Mayfield, 2018; Yunker & Hunt, 1976), while communication itself was notoriously absent. But the theories that did address communication did so from the perspective of uncertainty reduction, much like the literature in the field of organizational communication. Gutierrez-Wirsching, Mayfield, Mayfield, and Wang (2015) take note of this context when they state that MLT was proposed "in times when motivational theorists had their focus on uncertainty reducing managerial speech acts" (Gutierrez-Wirsching et al., 2015, p. 1239). Even today, Mayfiled and Mayfield (2018) contend that "a lot of managerial talk relies on task orientation, a more narrow spectrum of spoken language that sets goals and outlines task expectations rather than enhancing employee motivation" (J. Mayfield & Mayfield, 2018, p. 12). It was this narrow focus of language in motivation that prompted Sullivan to propose MLT as a way to broaden the perspective on which motivation was studied and understood (J. Mayfield et al., 1995).

Sullivan (1988) based his theory on psycholinguistics and speech act theory. He stated that the functions of language can be described by speech act theory's utterances and conceptualized the following three speech acts: Perlocutionary acts are those that focus on what the speaker hopes to accomplish, which Sullivan adapts in his theory as direction giving and uncertainty reducing speech: that which is used to reduce task ambiguity as well as clarify goals and rewards. Illocutionary acts are those that are focused on what the speaker is doing while he or she talks, which Sullivan adapts to his theory as empathetic language: the language of humanity or sympathy that happens every day (J. Mayfield, Mayfield, & Kopf, 1998; Sullivan, 1988). In the words of Sullivan, "It's not a case of a manager saying, 'Today, I'll be human.'" (Sullivan, 1988, p. 109). Finally, locutionary acts are those that are focused on the meaning of the words. Sullivan adapts these acts to his theory in the form of meaning making language. It helps the worker make sense of his or her environment through the explanation of its culture and norms (J. Mayfield et al., 1998; Sullivan, 1988).

According to Holmes (2012), "The concept of intention is key in understanding speech acts and how they differ from emotional reactions" (Holmes, 2012, p. 51). Fotion (2014) makes this distinction with the following illustration: “If I utter a series of unprintable expressions as, in total darkness, I futilely fumble to fit my key into the door lock, I am not using language intentionally. What I say counts as an event or an uncontrolled reaction, but not an act. But if I say, in a calm, clear, and deliberate voice, ‘There is a stranger at the door,’ ‘Please close the door,’ ‘You’re hired,’ or ‘Congratulations,’ I speak intentionally. As such each of these utterances is a speech act.” (Fotion, 2014, p. 5). It is this intention and deliberateness of the speech act that gives the utterances their mindfulness (J. Mayfield & Mayfield, 2018).

The importance of Speech in Motivating Language

A constant theme that appears throughout MLT literature is that of spoken language. In his article, Sullivan (1988) bases his conceptualizations on psycholinguistics and speech act theory and proposes that managerial communication can be categorized in terms of three *speech* acts. Indeed, the literature on motivating language highlights the importance of the *spoken language of leadership* as being of critical influence to worker outcomes, and it shows in how the training a leader in the strategic variance of speech has links to various outcomes (J. Mayfield et al., 1995). This is indeed further reiterated when J. Mayfield et al. (1998) conduct their second empirical study in the field of MLT, where oral communication takes center stage in the theoretical development stage as shown by the way in which they address the training in linguistic skills as well as interventions centered on conversational training objectives. In the words of the authors “motivating language theory (ML) hypothesizes that deliberate variance in leader *speech* can be used as a motivational tool to help employees meet desired organizational and personal objectives” (J. Mayfield et al., 1998, p. 236).

Critical Assumptions of Motivating Language Theory

Motivating language has four critical assumptions. First and foremost, a leader’s words and actions need to be congruent. Motivating language will only have the desired effect if a leader *walks the talk*. The second is that leaders must combine all three speech acts, or ML dimensions in a purposeful and strategic manner in their speech in order to reap the full benefits of motivating language. The third assumption is that the follower must correctly perceive and understand the message of the motivating language that the leader is transmitting. The fourth and final assumption is that these three types of speech encompass almost all important and work-related forms of leader-follower speech (Gutierrez-Wirsching et al., 2015; J. Mayfield & Mayfield, 2018; J. Mayfield et al., 1995; Sullivan, 1988).

As mentioned above, *leaders must walk the talk.* The process of doing so establishes credibility from the perspective of the follower: it is a manifestation a human inclination to look for sense making cues, when there is a mismatch between actions and words (J. Mayfield & Mayfield, 2018). In the words of Mayfield and Mayfield, “Talk is viewed as cheap when it conflicts with actions” (J. Mayfield et al., 1998, p. 237), and “Employees interpret leader speech within a behavioral context and, in cases of incongruity, tend to rely on actions in lieu of words” (J. Mayfield & Mayfield, 2007, p. 88). Holmes finds that phrases that describe the congruence and connection in a leader’s communications and actions are along the lines of “Leaders do what they say they will do,” “Leaders practice what they preach,” “Their actions are consistent with their words,” and “Leaders walk their talk.” (Holmes, 2012, p. 47).

M. Mayfield and J. Mayfield (2009) find initial support for his assumption when they conducted a study on the topic of the leader’s communication and behavior congruence using leader-member exchange (LMX) theory. In their conclusions, they state that “based on our results, leader communication can only be successfully translated into higher worker performance and Job Satisfaction through appropriate leader behavior. In short, it is not enough to simply talk a good game, leaders must be able to put this communication into concrete, positive leader behavior" (M. Mayfield & J. Mayfield, 2009, p. 79).

Holmes and Parker (2017) provide additional support for this assumption in their longitudinal study on the use of motivating language by school principals. They find "statistically significant correlations between behavioral integrity and motivating language, credibility and motivating language, and between behavioral integrity and credibility" (Holmes & Parker, 2017, p. 70). They also find that in each year, "behavioral integrity and credibility contributed significantly to the prediction of the principal's motivating language use" (Holmes & Parker, 2017, p. 70). They conclude that "behavioral integrity and credibility are integral to a leader's use of motivating language" (Holmes & Parker, 2017, p. 70).

The fact that Sullivan (1988) classifies leader-follower communication into three different types of speech acts or language did not mean that these dimensions were to be separate pillars in support of a larger construct; three different types of speech acts or language, each to be used separately. The use of all three dimensions of motivating language was crucial in Sullivan's postulation of his theory. Rather this classification arose from the need to highlight the fact that speech needs to be purposefully multifaceted. To emphasize this, Sullivan says "managerial influence on employee motivation through communication is a function of the variety of speech acts that are employed. The more varied the speech acts, the greater the likelihood that the manager will influence employee motivation. If multiple language tools are available, the manager should use them to attain the maximum control of the motivational communications process." (Sullivan, 1988, p. 104). He also uses the following statement from a supervisor to an employee as an illustration: "Ed, I'm just so happy to tell you that your chances of promotion will be good if you do well on this project," (Sullivan, 1988, p. 108). This statement is an example of how a leader's communication can be both uncertainty-reducing (reducing the uncertainty of a promotion) as well as meaning-making (by helping Ed construct an image of himself within the organization) simultaneously. Mayfield and Mayfield give a similar hypothetical scenario: "a leader may use multiplex forms of motivating language at the same time; that is, a boss gives a subordinate task requirements (direction-giving language) that include cultural norms of delivery such as a required presentation on an organization's intranet (meaning-making language) along with verbal reassurances of task encouragement (empathetic language)" (J. Mayfield & M. Mayfield, 2009, p. 460).

In fact, Sullivan proposed the strategical coordination of the three dimensions of motivating language in order to achieve the best possible results, and now there is empirical support for his proposal (J. Mayfield, Mayfield, & Sharbrough, 2015). J. Mayfield and Mayfield (2018) propose:

> most likely happens over time and is influenced by organizational events. For instance, a leader would probably use more meaning-making language with new hires and during times of organizational transition. During periods of more organizational stability, direction-giving and/or empathetic language might prevail. Moreover, a kind and caring boss can give lousy directions and fail to communicate how a task aligns with the overall company objectives. In such a case, we predict that there will be weaker positive outcomes, if any. Fortunately, we believe that motivating language is a learned skill, so its appropriate combinations can be acquired through training and development. (J. Mayfield & Mayfield, 2018, p. 17)

The importance of the integration of these three dimensions cannot be stressed enough because "a leader's strategic communication is only expected to have a positive and significant impact when all three factors are used in a coordinated effort" (M. Mayfield & Mayfield, 2004, p. 47).

The last two assumptions are closely related: for a motivating language to be effective, the follower must understand the message that is being communicated by the leader, since motivating language encompasses most of the leader to follower communications (Gutierrez-

Wirsching et al., 2015; J. Mayfield & Mayfield, 2018; J. Mayfield et al., 1995). The approach that the research has adapted to incorporate this assumption of understanding is to measure motivating language from the perspective of the follower. Since the leaders must necessarily be aware of the needs of their followers to use the dimensions of motivating language properly and effectively, an implicit feedback loop is included in the model. The research has not explored this feedback loop (J. Mayfield & Mayfield, 2018).

In order to achieve the goal of broadening the scope of the language and to address the largely overlooked dimensions of communication, Sullivan adapts these three speech acts and proposes that most leader-follower talk can be classified as perlocutionary (uncertainty-reducing), locutionary (meaning-making), or illocutionary (human-bonding) speech acts (J. Mayfield et al., 1998).

Meaning-Making Language

Meaning-making language serves to illuminate and clarify organizational culture and other related norms (Holmes, 2012) as well as facilitating the building of cognitive schemas that help guide the follower in framing their job duties and functions in the organization's cultural context (Gutierrez-Wirsching et al., 2015). The expectation is that by understanding these cultural norms, the follower will perform their job better by adapting to "methods that will be more effective and efficient within the given organizational setting" (M. Mayfield & J. Mayfield, 2009, p. 67). It helps align higher purpose at work with a follower's personal goals and helps the person know that they and their talents are uniquely appreciated and how they can be guided toward organizational contribution. This integration of higher purpose in work echoes Frankl's logotherapy, where the primary driving force of a person is the search to find meaning in life (J. Mayfield & Mayfield, 2018).

J. Mayfield and Mayfield (2018) propose that leaders must first overcome their own personal psychological noise so that they can be properly aware of their followers' aspirations and strengths. This is paramount if the leader is to be able to communicate respect for a follower's abilities and be able to suggest guidance that overlaps with the organization's goals. In order to achieve this, the leader must be purposeful in drawing a clear image with his or her words of the values, vison, and cultural norms of the organization; one that is coherent with the values and aspirations of the follower.

Meaning-making talk is often informal in nature and conveyed through stories and metaphors. This talk can include stories about people who have gone above and beyond the call to fulfill a worthwhile organizational purpose as well as the stories of those who have failed. These tales are meant to inform a follower "about cultural rules that must be respected in order to succeed. When a boss tells an employee that the CEO's annual dinner is a command performance or that a representative from information systems must be included in the new product task force, meaning-making language is happening" (J. Mayfield & Mayfield, 2018, p. 13).

J. Mayfield and Mayfield (2018) state that meaning-making language is best understood through the use of examples, and they categorize the kinds of examples that can be used by types of a leader's skills in motivating language. *Cultural storytelling* is the most common kind of example, such as that of people in the organization that have succeeded at a task, and what the rewards or punishments entailed. Allegories and metaphors can also be used for this talk at times. The authors use the following illustration: "Accountants should not be like foxes in the hen house" (emphasizing the importance of ethics to a junior CPA). Or "We are more like tortoises than hares" (advocating an organizational strategy for thoughtful consultation with customers versus aggressive marketing to a new client service representative)" (J. Mayfield &

Mayfield, 2018, p. 27).

Another category is *linking personal values to work/organizational values.* In order for the leader to be able to do this, he or she must first invest time and effort and listen attentively to the followers to find out what their personal values are (J. Mayfield & Mayfield, 2018). While it is true that that motivating language does not study the follower to leader language, it is implicitly clear that a leader must first get to know the follower in order to correctly communicate meaning. It therefore makes sense that motivating language embraces the theory of respectful inquiry: it proposes that a leader's interpersonal communication skills such as posing open ended questions, attentive listening, and soliciting and supporting honest follower feedback will elicit the growth of a follower's intrinsic motivation (Van Quaquebeke & Felps, 2018).

The next category is that of meaning-making language used in the context of *organizational/cultural changes.* Times of organizational and cultural change can be times of uncertainty and stress, and it is the role of the leader to communicate to the follower how the changes will affect them and their roles (Holmes, 2012). J. Mayfield and Mayfield (2018) state that "Without understanding an organization's vision, employees can't fulfill it" (J. Mayfield & Mayfield, 2018, p. 29). Kotter (1998) lists "Undercommunicating the Vision by a Factor of Ten" as reason number four on his *Harvard Business Review* article titled *Why Transformation Efforts Fail*. He further states that "Without *credible* communication, and lots of it, the hearts and minds of the troops are not captured." (italics added for emphasis not in the original article) (Kotter, 1998, p. 63). Leaders that are high users of motivating language will explain these changes to their followers while prioritizing transparency, timing, and vision framing, and do so in a timely manner (with immediacy) that will keep the informal communication channels of the organization in check (J. Mayfield & Mayfield, 2018).

Another category of meaning-making language is referred to as *behavioral guidelines/artifacts*. They show how a leader coaches the follower in rules of organizational etiquette that the follower must respect to accomplish task goals in an effective manner. One basic from of this communication is the outlining of a desirable comportment. J. Mayfield and Mayfield (2018) cite an example about a boss that one of them had: “The president's annual party is a command performance where a *no show* will raise eyebrows . . . And no blue jeans in the office at any time.” (J. Mayfield & Mayfield, 2018, p. 30). The follower may or may not agree with such rules, but the point is that they are clear; if the follower does not agree with the rules, then he or she may not be a good fit for the organization, and it is difficult to succeed if this fit is not a good one. These behavioral guidelines may also include mentoring on how to handle work place politics, such as tips on who are the key stakeholders and how to address them, which can help optimize cooperation (J. Mayfield & Mayfield, 2018).

The next categories to be discussed will be those of *express collective, higher purposes,* and that of *task significance/individual organizational contributions*. These two categories of meaning-making speech are closely related, since they can be seen as different aspects of the same aspiration: to serve a higher purpose. The first category captures this aspiration at more of a macro level, while the second does so at a more individual level.

A meta-analysis of Gallup organizational research indicates that most employees sincerely desire to contribute to a purpose greater than themselves (Harter, Schmidt, & Keyes, 2003; J. Mayfield & Mayfield, 2018). This finding agrees with Frankl’s logotherapy and its leadership application, logoleadership (J. Mayfield & Mayfield, 2018). Mayfield and Mayfield mention that for this type of meaning-making “a tantalizing portrait of the organizational vision is paramount in leader-to-follower communication. This vision should be inspirational and transcend financial and productivity goals" (J. Mayfield & Mayfield, 2018, p. 30). Leader talk for this from of meaning-making language should evoke a higher purpose but also connect with the follower at the personal level of his or her aspirations for meaning.

The last category of speech for meaning-making language is *Innovation:* the use of meaning-making language encourages "garden variety creativity." The research has shown that the use of meaning-making language fosters the creation of improvements to routine jobs (M. Mayfield, 2009). This creativity is constructed through the leader's spoken emphasis on the importance of innovation for the values of the organization.

Empathetic Language

The purpose of empathetic language in motivating language is to reaffirm a follower's sense of self-worth as a human being (Gutierrez-Wirsching et al., 2015) through a leader's use of emotional and humanistic language that creates and strengthens the emotional bonds between the leader and the follower (Holmes, 2012). It lets the follower know that he or she is valued as a human being and not just as an organizational asset because of their work-related abilities (J. Mayfield & M. Mayfield, 2009). "Through empathetic language, a leader bonds with a follower in a wide array of scenarios" (J. Mayfield & Mayfield, 2018, p. 14).

To paraphrase Sullivan, empathetic language is not communicated by using a strategy, but simply by being human and displaying a natural and empathic behavior (Sullivan, 1988). As he said, a leader does not just decide one day and say: "Today, I'll be human" (Sullivan, 1988, p. 109). In order to become "more human" in the eyes of the follower through such openness, the leader must be willing to lower the power differential with the follower in order to identify the follower's experience. Empathetic language can be expressed in positive or negative situations, such as a "Good job!" comment upon a job well done, as an expression of support in the face of a challenging situation or personal frustrations, or as validation over a stressful situation at work (J. Mayfield & M. Mayfield, 2009; J. Mayfield & Mayfield, 2018). It also includes talk that expresses "support, compassion, and shared happiness for personal life events. For example, a leader using empathetic language would communicate heartfelt concern about a serious illness in a follower's family. Another type of empathetic message would be to congratulate a follower about their child's scholarship award" (J. Mayfield & Mayfield, 2018, p. 15).

In a way similar to meaning-making language, empathetic language can be best understood by examples that can be categorized according to the evolution of the leader's use of the breadth and depth of language. The first of these categories is *politeness/cordiality* and reflects the show of civility and respectfulness toward followers. Not only is the lack of civility, or uncivil behavior, in the workplace associated with various negative organizational outcomes, but it sets an example for the follower's behavior. To promote civility and respectfulness a leader must articulate politeness through the use of cultural norms of good manners with followers, which in most cases includes a friendly greeting at encounters (J. Mayfield & Mayfield, 2018). "Harsh language is not permissible. And verbally interrupting a subordinate should only be done in extenuating circumstances" (J. Mayfield & Mayfield, 2018, p. 42).

Speech categorized as *work empathy* happens when a leader "communicates that a follower's job satisfaction is a priority" (J. Mayfield & Mayfield, 2018, p. 42). These messages should be nonjudgmental and involve genuine listening about how an employee feels about their work.

Another category is that of the language that is used as spoken support in the case of *achievements and setbacks.* While in the case or achievements, verbal congratulations should be given, it is important to keep in mind that setbacks will eventually happen to those who put forth genuine effort. Leaders that use empathetic language efficiently not only encourage dispirited followers, but use language to help them learn from their negative experiences (J. Mayfield & Mayfield, 2018).

A follower's *personal goals* are embraced in empathetic language in a manner similar to that in meaning-making language: a leader has to actively listen to the follower to identify what his or her goals are and to offer encouragement (J. Mayfield & Mayfield, 2018). According to Mayfield and Mayfield, although "The benefits of earnest praise are enormous. Upbeat connections at work promote several desirable outcomes, including better physical and mental health, performance, resilience, commitment, and engagement" (J. Mayfield & Mayfield, 2018, p. 43); the praise must be genuine and specific, or they may be perceived as not authentic. It should also vastly outnumber the number of negative comments (about 5:1) (J. Mayfield & Mayfield, 2018).

In order for emotional bonding to occur between leaders and followers, leaders must recognize and support the *personal experiences* of followers, so that the "whole person" is encouraged to show up to work. This sort of talk will express sincere congratulations for positive accomplishment and compassion for negative life events. To achieve this level of empathetic communication, leaders must be vigilant in their attentiveness and listening that can encourage their followers to share their feelings via inquiry, setting of ground rules, or expressing relevant personal emotions of their own. All while maintaining healthy boundaries and realizing that leaders should not fall into a role they are not trained for, such as counselor or psychotherapist (J. Mayfield & Mayfield, 2018).

In the context of empathetic language, *effort* is that leader speech that is aimed at applauding a follower's work initiative that goes above and beyond that of task completion, whether this leads to desired results or not (J. Mayfield & Mayfield, 2018). “For example, a high performing research and development professional may discover that a targeted new product will not be marketable before it is launched. A leader using strong empathetic language will commend her or him for diligence” (J. Mayfield & Mayfield, 2018, p. 44).

Finally, the last category is that or work *barriers* that refer to messages of support (as opposed to blame) from a leader when the follower encounters challenges at work, such as a setback, without dictating how the follower should feel. In some cases, a negative emotional response is natural, such as the cancellation of a project (J. Mayfield & Mayfield, 2018).

Direction-Giving Language

The third and final dimension of motivating language is direction-giving language. It dominates most leader talk for a good reason: its role is vital in effective leader communication. After all, no organization can survive without clear instruction on how to set goals, and instructions on how to achieve the tasks that these goals entail, or what the functions and rewards of one’s job are (J. Mayfield & Mayfield, 2018). “Scholars have consistently argued that direction-giving functions such as information sharing, facilitating optimal performance, goal setting, and establishing reward contingencies—then administering them—are critical to effective leadership” (J. Mayfield & Mayfield, 2018, p. 51).

The main purpose of direction-giving language is to reduce uncertainty, increase knowledge (Gutierrez-Wirsching et al., 2015), and to communicate structure after the fashion of the Ohio state studies and path-goal theory (J. Mayfield et al., 1998). In other words, it is the key to get things done in an effective and efficient manner by dispelling ambiguity through transparency (J. Mayfield & Mayfield, 2018). In the words of Sullivan, “As perlocutionary communication, the words reduce the worker's uncertainty about the relationship between an action and the attainment of a need, value, or goal, and they trigger a mental calculation that presumably results in an intention to expend a specific level of effort. Most motivation theories treat utterance in this way" (Sullivan, 1988, p. 108).

Contrary to some perceptions, direction-giving language does not need to be delivered in an authoritative manner; quite the contrary, it is oftentimes more compelling when spoken with genuine humility. The leader articulates and communicates the necessary information for performing the job, such as the clarification of goals and the rewards associated with reaching them. Additionally, it will also involve feedback that when given by a leader with good motivating language skills will lead to improved learning as well as greater self-efficacy and performance, which in turn leads to reduced job ambiguity and stress (J. Mayfield & Mayfield, 2018). Positive outcomes such as increased self-efficacy and performance can lead to being trusted by the supervisor, and "Greater trust can be equated with perceived caring by the leader. In this way, direction-giving talk is related to empathetic language. When supervisor empathy is felt, followers are more likely to be committed to their jobs" (J. Mayfield & Mayfield, 2018, p. 52). It should also not be surprising that direction-giving language should be linked to the ethical behavior of the leader, since it involves transparency and the sharing of power. Leaders who make ethical decisions often involve their followers in decision-making that thus inherently lowers the power differentials. (J. Mayfield & Mayfield, 2018).

Mayfield and Mayfield succinctly explain the use of direction-giving language: "An example of direction-giving language happens when a boss details an assignment to an employee including how it fits in to the big organizational picture, what successful assignment completion looks like, how the results will be measured, processes and policies that should be followed in task fulfillment, preferable and acceptable time frames for assignment delivery, and reward contingencies" (J. Mayfield & Mayfield, 2018, p. 15). As mentioned previously, the process should also include constructive feedback about tasks.

As with other dimensions of motivating language, direction-giving language can be separated into progressive categories. In this case they are arranged starting from information dissemination and culminating with empowerment. The first category is *basic work requirement/procedures* and refers to communications of transactional leadership that are related to necessary operations. Examples are general task requirements, organizational rules and regulations, and ethical and safety policies (J. Mayfield & Mayfield, 2018).

The next category is *innovation* and departs form needed facts and progresses to coaching and knowledge sharing that promotes innovation as well as encouragement about risk taking and learning form mistakes. *Performance feedback* is a related category that has long been difficult for leaders as well as followers. Some reasons for this difficulty may be that it is not timely enough, focused enough on the particular issue that is controllable by the follower, framed with corresponding positive feedback, or accompanied by steps to remedy the issue. The category of *available resources* refers to providing the follower with the knowledge about the resources that are available and may need to be used to complete a particular task (J. Mayfield & Mayfield, 2018).

The category of *roles* is about informing a follower what his or her job involves, and how it relates to other jobs in the organization. *Task clarity* is a more focused application of the above, removing uncertainty and clarifying the tasks that the role involves. The next category of *priorities* is related and crucial to the previous two concepts: In order for the *role* to be performed properly, the *tasks* need to be clear as well as the *priority* that each of these tasks has. Lack of clarity in task *priority* can lead to low performance and decreased self-efficacy. Last of all, it is important to highlight that *tasks* are closely related to the last category: *goals*. Goals are not just about assigning a task and expecting to be simply accepted; it should be reasonably articulated and clearly specified in multiple dimensions (J. Mayfield & Mayfield, 2018).

Reward is another category of direction-giving language and states the reward contingencies for meeting certain terms. The clarification of rewards should paint an unambiguous image of what the reward is going to look like and should be followed through on. The category of *autonomy/authority* is related to the previous concept, since it is a form of reward in of itself. The delegation of authority not only brings inspiration and agility to operations but must necessarily be accompanied by further clarification of task as well as breadth of authority and decision-making power (J. Mayfield & Mayfield, 2018).

The Synergy of Motivating Language

All three dimensions of motivating language must be used strategically in order for its full benefit to be manifest to the leader, follower, and the organization. Each dimension of motivating language has a different role that cannot be replaced by the use of the others, and a deficit in one will minimize the benefits of using the other dimensions. Therefore, in order for a leader’s speech to become quality motivating language, all three forms of speech must be used in an interlinked way and not treated as three separate kinds of speech: motivating language is synergistic in nature. Although each dimension has a different role to play, workplace activities usually need to be addressed by more than one type of motivating language. While direction-giving language can be used to explain job duties, it cannot provide a person with a sense of how they fit in the organization or help them fit into the organizational culture. In a similar fashion, expressing empathy about the challenges of trying to fit in the new role in the organization can seem as insincere unless it is accompanied by specific advice on how to actually achieve it. J.

Mayfield and Mayfield (2018) emphasize the importance of the strong use of motivating language when they say that: “A strong use of a single Motivating Language facet can increase worker outcomes – better direction-giving language helps workers to set goals, empathetic language use can increase job satisfaction, and meaning-making language can increase loyalty. But independently, each facet fails to cover the full range of workplace communication, and so its effect remains limited. Each ML facet interlocks to support the others. A weakness in one area lessens the strength in another.” (J. Mayfield & Mayfield, 2018, p. 67).

Media Naturalness Theory

The importance of face-to-face communication is found in multiple streams of literature. One of which is MLT. In the case of human evolution-related research, theories converge on the view that the human brain has evolved to cope with problems that occurred in an intermittent manner in our evolutionary past (Kock, 2002). This is the main point of media naturalness theory: The human communication apparatus “is better designed for the solution of communication problems found in our remote evolutionary past than for those in today’s world” (Kock, 2004, p. 332), such as communicating using modern technology, writing included. This human communication apparatus consists of a web of facial muscles that gives us a large range of facial expressions, a uniquely placed larynx that gives us an unusually wide tonal range that enables us to speak, and specialized brain circuitry to handle these communications (Kock, 2004).

Previous theories of CMC have identified face-to-face (FTF) communications as having more “social presence” or being “richer” but have done so without an explicit theoretical foundation. Further, some of their conclusions appear to be at odds with the seemingly ever increasing offerings and use of CMC (Kock, 2004). Various CMC were covered in the introduction section of this paper, including their theoretical underpinnings as well as their resulting shortcomings that stem from their implicit assumption about the nature of organizational communication as being primarily equivocality-reducing language.

Another theory that the research has used as a frame of reference is social presence theory (SPT). It was not covered in the introductory section, since it was proposed well before the internet and modern telecommunications (1976) (Kock, 2004). It bears some similarity to MRT in the sense that both classify communication media along a one-dimensional continuum. While for MRT, this was "richness;" for SPT, it is known as "social presence." Much in the same manner that that MRT defined richness as being a characteristic of the CMC channel, SPT defines social presence as being a characteristic of the communication channel (Gunawardena, 1995), which leads some to state that MRT's construct of richness can be seen as a more elaborate form of SPT's social presence construct (Kock, 2004). In this manner, social presence can be seen as "the degree to which a person is perceived as a 'real person' in mediated communication" (Gunawardena, 1995, p. 151). When faced with empirical findings that are inconsistent with SPT while studying various online learning scenarios, its proponents have proceeded to incorporate a socially derived perception component: Social presence through CMC that is low in social context cues (low social presence) because the perception of social presence depends on the kind of interactions that are being conducted and the moderator's ability to facilitate those interactions (Gunawardena, 1995). As a brief reminder, the introduction section covered how CET sought to refine MRT's inconsistent predictions of media choice by incorporating a socially derived perception component (channel expansion) (Carlson & Zmud, 1994).

The increase in CMC research and the corresponding growth in the body of data available “drove systematization attempts based on the development and refinement of theories that could be used to classify and explain empirical findings” (Kock, 2004, p. 328). This growth led to a dramatic increase in the number of theories that attempted to explain media use in the light of new phenomena of CMC behavior (Kock, 2004). Some of these, such as social influence (Fulk, Schmitz, & Steinfield, 1990) and social construction of realities theories (A. S. Lee, 1994), emphasize the strengths of social influences such as peer pressure, context specific mental schemas, and cultural differences making the argument that these factors may have a stronger effect on behavior than media characteristics. In doing this, a theoretical gap was left in these theories where they failed to explain the limited findings that did support MRT and its related theories, which in turn led to countercriticism from the supporters of said theories (Kock, 2004). This heated debate led to SPT and MRT being labeled as “rational choice” theories, which became a generic label to encompass any theory that emphasizes the rational choice of technology and places little or no emphasis on social influences. With the emphasis of a flawed or “deterministic” view of CMC behavior, social theorists have rejected the theories entirely, and “convincing theoretical arguments have been put forth showing that rational choice theories cannot be effectively combined with social theories without radical revisions” (Kock, 2004, p. 329).

The CMC theories that have been discussed in the previous two sections have by and large taken for granted that face-to-face is better; they have not explored the reason why. A simple answer would be that we are naturally predisposed to it, but that would leave the deeper question unanswered: Why does evidence seem to indicate that we are predisposed to communicate face-to-face? In research terms: What is the missing variable? The media naturalness theory argues that it is human nature: “the genetic makeup that plays a key role in defining our human communication apparatus" (Kock, 2004, p. 329).

The Evolution of the Human Communication Apparatus

An important tenet in MNT is that according to Darwin's theory of evolution by natural selection that was proposed in 1859, "our biological communication apparatus has developed through evolutionary adaptation over millions of years" (Kock, 2004, p. 329); it, and ultimately the genes that regulate it and its development, influence our communicative behavior and thus ultimately our CMC behavior (Kock, 2004). Kock (2004) uses the term "biological communication apparatus" to refer to the parts of our brain and body that are used to communicate. He incorporates what Lieberman (2000) calls the "neural functional language system" of humans with their distributed sets of brain circuits, and the body structures that are controlled by our brain in the communication process, both voluntarily and involuntarily. It also includes the expressive and perceptive parts of our biological communication apparatus (Kock, 2004).

Darwin's theory of evolution by natural selection and the genetic principles of Gregor Mendel were later unified in a theoretical framework that is now known as *evolutionary synthesis* (Mayr & Provine, 1998). This framework is supported by three pillars: inheritance, mutation, and natural selection (Kock, 2001a). Biological anthropology uses this framework with social ethnography to argue that humans and other species have evolved according to the fundamental laws of evolution (Boaz, 1997), which for humans includes human communication apparatus. Thus, through the course of millions of years, genetic mutations that proved advantageous to the survival of early humans were inherited by their progeny, including those of the biological communication apparatus (Kock, 2004).

Kock (2004) proceeds to build the case for MNT from an evolutionary perspective by arguing that the two interdependent principles of *repeated use* and that of *brain-body coevolution* that are widely used by evolution theorists can be used to show that the development of the expressive and perceptive parts of our human communication apparatus and the brain functions that are associated with them “must have been designed primarily for face-to-face communication” (Kock, 2004, p. 331). The principle of *repeated use* argues that there is a correlation between the number of generations that a specialized set of organs is used for a particular purpose in a relatively stable environment and the extent of its evolutionary optimization. Therefore, the fact that the human biological communication apparatus is so highly specialized and unique is an indicator of the length of time (generationally speaking) that our ancestors spent communicating face-to-face. Relatedly, the principle of *brain-body coevolution* argues that both the body and the brain coevolve in a closely matched way. In this manner, the gradual evolution of certain highly specialized characteristics such as a complex web of facial muscles and an highly customized larynx with an unusual placement must necessarily be accompanied by specialized brain functions to process and control them (Kock, 2004).

It is in this manner that Kock arrives at the conclusion that the human brain has evolved “to excel in face-to-face communication” (Kock, 2004, p. 331) and that symbolic language, such as writing, was developed as a tool to solve problems that humans were not evolutionarily equipped to solve: the preserving of knowledge. Since our biological communication apparatus does not posses brain circuitry to process communication in a form that is different than face-to-face communication, using such unnatural forms of communication will pose a *cognitive effort* (Kock, 2004).

The Psychobiological Model

The psychobiological model is Kock’s grouping of four propositions into a design that is internally consistent and falsifiable (Kock, 2004) and that facilitates the development of future empirical research in the field. Kock explicitly states that one important feature in the model is its focus on cognitive effort rather than media choice or behavior. A second important feature is that the model is "largely *task independent* within the scope of collaborative tasks" (Kock, 2004, p. 333). It is this strong theoretical support that allows MNT to take a markedly different approach to previous CMC theories; approaches where other theories propose that media choice or behavior is a function of the collaborative task, MNT proposes that cognitive effort is a function of media naturalness. In this manner, Kock postulates the first of four propositions in MNT.

Media Naturalness Proposition: *"Decreases in the degree of naturalness of a CMC medium lead to increases in the degree of cognitive effort required from an individual to use the medium for communication to accomplish a collaborative task"* (Kock, 2004, p. 333).

A related concept to be above proposition is that of medium naturalness that Kock defines as

> the degree of naturalness of a CMC medium can be assessed based on the degree to which it incorporates five key elements of face-to-face communication: (a) colocation, which would allow individuals engaged in a communication interaction to share the same context, as well as see and hear each other; (b) synchronicity, which would allow the individuals to quickly exchange communicative stimuli; (c) the ability to convey and observe facial expressions; (d) the ability to convey and observe body language; and (e) the ability to convey and listen to speech. (Kock, 2004, p. 333)

He also clearly defines cognitive effort as "the degree of schema use, and, in the case of learned tasks that require cognitive adaptation, to the degree of schema reconstruction and development required to accomplish a certain cognitive task" (Kock, 2004, p. 333).

He also states that while from a biological perspective this construct can be seen as related to brain activity, it is usually assessed through measures of perceived cognitive effort (Kock, 2004).

The next proposition in the model is the speech imperative Proposition, which builds upon the concepts of the evolutionary cost of adaptations and argues that characteristics that are evolutionarily costly to develop are also costly not to use. Kock (2004) proceeds to build a formative proposition related to media naturalness. Kock argues that the development of the human larynx came at an evolutionarily expensive cost: the same low placement that is necessary for the increased tonal range that is required for speech also presents an increased risk of choking on food and drink. None of the other expressive or perceptive components of the human communication apparatus appear to have a similar evolutionarily high cost. Therefore, the logical conclusion is that not using speech is more costly than not using any of the other expressive or interpretive components of the biological communication apparatus, which leads to the second proposition (Kock, 2004). The second proposition "would suggest that suppressing the ability to convey and listen to speech would substantially affect the naturalness of a medium, more than suppressing the ability to use facial expressions and body language, which should in turn be observed in variables directly or indirectly associated with cognitive effort." (Kock, 2004, p. 335).

Speech Imperative Proposition. " *The degree to which a CMC medium supports an individuals' ability to convey and listen to speech is significantly more important than the other elements of the expressive-perceptual dimension in defining the degree of naturalness of the medium."* (Kock, 2004, p. 335).

The third proposition of the model is the cognitive adaptation Proposition. Kock (2004) takes a cue from the field of evolutionary biology and uses its well-documented finding in the field of CMC: “the human brain is the most ‘plastic’ in the animal kingdom” (Kock, 2004, p. 336). This plasticity, which itself is an evolved characteristic, is what gives humans the ability to learn by modifying certain parts of the brain, most notably the neocortex. These learned schemas can cover a wide variety of learning topics, including CMC (Kock, 2004). This concept of schema alignment is similar to the proposals in CET (Carlson & Zmud, 1999) and MST (Dennis et al., 2008). It can explain why a person’s attitude toward a form of CMC tends to change over time.

Cognitive Adaptation Proposition. *“Increases in the degree of cognitive adaptation to a CMC medium lead to decreases in the degree of cognitive effort required from an individual to use the medium for communication to accomplish a collaborative task.”* (Kock, 2004, p. 336).

Kock defines the related construct of cognitive adaptation in the context of CMC studies as “the level of schema development associated with the use of a particular CMC medium to per- form collaborative tasks” (Kock, 2004, p. 336). He also states that cognitively adapting to a CMC is expected with repeated use of the medium. Thus, a person’s degree of cognitive adaptation to a particular CMC can be assessed through the amount of training, repeat use in collaborative tasks, or indirectly through self-efficacy perceptions (Kock, 2004).

The fourth proposition in the model is related to the previous one: the schema alignment proposition. Kock proposes that another consequence of having a highly plastic brain is that people will have different learned schemas, and that people from different cultural backgrounds have different mental schemas that can influence the way they interact with a form of CMC. This alignment (or lack thereof) between individuals engaged in communication will affect the cognitive effort involved in the use of a form of CMC to collaborate with others (Kock, 2004).

Schema Alignment Proposition. *"Increases in the degree of schema alignment between any two individuals using a CMC medium lead to decreases in the degree of cognitive effort required from each individual to use the medium for communication to accomplish a collaborative task."* (Kock, 2004, p. 337).

Kock proceeds to define schema alignment as "The degree of schema alignment between two individuals can be assessed based on knowledge and skill tests associated with the specific task they intend to perform collaboratively." (Kock, 2004, p. 337). This concept of task related shared schemas allows MNT to be a task independent theory within the scope of collaborative tasks (Kock, 2004).

Contributions of Media Naturalness Theory and Differences with Other Theories

Kock (2004) mentions three key differences that the psychobiological model has with MRT and SPT. The first difference is that MNT focuses on the human biological communication apparatus, while other CMC theories focus on the communication medium, and consequently its characteristics. The second difference is that MNT does not associate low levels of medium naturalness with behaviors or attitudes toward the form of CMC, but rather with the high cognitive effort during the communication. This is related to the third difference, which is an implication of the previous one. The implication is that a super-rich form of communication such as virtual or augmented reality would actually pose an added cognitive effort due to the fact that it departs from the "natural" by adding more communication (Kock, 2004).

The psychobiological model's theoretical foundation provides a solid base on which to build a scale for communication media. It allows the researcher the possibility of gaining insight not only into some of the seemingly contradictory findings in the area of CMC research, but also into why CMC has face-to-face communication at its core and yet fails to explain the reasoning behind it. This foundation also isolates the influence of learned schemas and instinctive schemas on CMC behavior. Even though MNT has clearly made progress in the field of CMC, Kock states that it is "inherently limited and thus needs to be combined with other theoretical models to fully explain CMC behavior" (Kock, 2004, p. 341). This theoretical integration with MLT will be explored in a later section of this study.

In Support of Media Naturalness Theory: Choice Theories and Studies

In the field of CMC research, several theories are similar to MNT but albeit sometimes with a different underlying rationale. For instance, Daft et al. (1987) argue that it is better to approach equivocal tasks through FTF communications, which is not incompatible with MNT's media naturalness proposition (Kock, 2004). Similarly, Carlson and Zmud (1994), and Kock (Kock, 2004, 2005a) make similar arguments with CET and the cognitive adaptation proposition respectively: as a person become more familiar with a form of CMC over time, they will adapt to it (MNT) or perceive it as less lean (CET). One important point that must be clarified regarding this similarity is that where in CET the "perception of richness" happens with the person that is receiving the message (Carlson & Zmud, 1999), the burden of adaptation in MNT is on the person sending the message (Kock, 2007).

A more modern and less well-known theory is media synchronicity theory, which also has some similarities with MNT. The concept of parallelism in MST (Dennis et al., 2008) can be seen as a special extension of the "super-rich media" argument made by Kock in his proposal of the psychobiological model (Kock, 2004). Similarly, rehearsability and reprocessability in MST (Dennis et al., 2008) can be seen as adaptations of Kock's compensatory adaptation to characteristics of the medium (Kock, 2004). Finally, the concept of media appropriation (Dennis et al., 2008) can be seen as a special case of compensatory adaptation (Kock, 2004).

Recent neurological research has found that when a speaker's spatiotemporal brain activity is used to model the listener's brain activity, the speaker's activity is spatially and temporally coupled with the listener's activity. The authors also find that the extent of this speaker-listener neural coupling predicts the success of the communication (Stephens, Silbert, & Hasson, 2010). These findings can be seen as support for the schema alignment proposition of MNT which argues that higher alignment will lead to decreased cognitive effort in the communication process (Kock, 2004). Further experimental research into this topic has found that significant increases in neural synchronization occur in face-to-face dialog but not in other types of communication, such as back-to-back dialog, back-to-back monologue, or face-to-face monologue. This finding highlights the importance of a turn-taking behavior during communication (Jiang et al., 2012). These findings seem to support MNT's principal tenet: that humans have evolved over millions of years to communicate face-to-face (Kock, 2004).

The empirical research also finds support for the schema alignment proposition in the business environment. Kock (2004) shows that information overload has a cultural factor (power distance) that has more explanatory power than the volume of information or number of informational transactions. Thus, he confirms the proposition from the perspective of culture as a mental schema (Kock, 2004). Galegher and Kraut (1990) offer support for the speech imperative proposition. Their study shows that a marked difference exists between subjects that communicate with text-based CMC compared to those that use face-to-face or audio accompanied with text-based CMC; they find small differences between those that use face-to-face communication and those that use audio accompanied with text-based CMC.

Media Naturalness as a Moderator of Motivating Language.

In light of this, the fact that the research finds face-to-face communication as superior or preferable to various forms of e-communication in certain scenarios should not be surprising. This perspective is present in previous communication theories and the subsequent research. However, this perspective has resulted in apparently contradictory findings such as in MRT (Kock, 2004, 2005b, 2009; Kock, Verville, & Garza, 2007; Kupritz & Cowell, 2011; C. Lee, 2010) and CET (Kock, 1998, 2005a), while the SPT's popularity and continued evolution has made it a challenge to define the concept of social presence (Lowenthal, 2010). One of the more popular concepts in this area is the one emerging from the MRT that affirms that face-to-face is the logical medium of choice for coordinating complex tasks since it reduces communication equivocality. Evidence has since shown that things are not quite as straight forward, since contrary to what was previously hypothesized, managers and their subordinates have proved themselves to be able to handle complex tasks via email (Markus, 1994). Subsequently, Kock addresses this dilemma in MRT first by postulating that what face-to-face communication reduces is communication ambiguity (Kock, 2004) and the possibility of misinterpreting social cues (Kock, 2005b). At the same time, the research shows that certain things are better communicated face-to-face, such as feedback that involves constructive criticism for which the tone of voice, body language, and facial expressions can serve to soften the tone of the conversation (Kock, 1999). These findings are in line with more recent research that finds "a tendency for unpleasant emotions such as anger and anxiety to increase when emotional cues transmitted are low" when comparing face-to-face versus e-mail communication in their experiment. The authors also find that "low degrees of emotional cues transmitted between senders and receivers in e-mail communication tend to cause some misunderstanding" (Kato, Kato, & Akahori, 2007). Related research has also shown that individuals still value face-to-face communication under certain scenarios, such as when they are receiving information that is perceived as private, personal, or sensitive (Kupritz & Cowell, 2011).

Conversely, there are other types of communication for which leaner forms of e-communication are just as good as face-to-face communication, such as “meeting times, training times, and information with numerous details” (Kupritz & Cowell, 2011, p. 54). In some cases, communication is improved using email, for example (Kock, 2005b; Kupritz & Cowell, 2011). While it is true that employees want high tech communication, it is also true that they also want personal contact with managers (Kupritz & Cowell, 2011).

My study therefore attempts to address the dilemma of the aforementioned contradictory findings in the current literature stream by focusing on a specific form of communication (motivating language) and analyzing it through the lens of MNT. The advantage of using MNT is that it does not state that a certain medium is better suited to a task than another, but rather that their degree of naturalness differs. Therefore, it does not address the issue of communication medium choice but allows the researcher to study the entirety of the supervisor-subordinate communications as a stream that is composed of various media and to measure its degree of naturalness as a whole. Since MLT is theoretically defined as oral, I expect to find that as the degree of naturalness decreases in the communication stream, the effect of motivating language on subordinate outcomes diminishes.

CHAPTER III

HYPOTHESES DEVELOPMENT

This chapter of the study is divided into confirmatory and exploratory hypotheses. The purpose of setting a clear boundary between previously supported findings and the study's original research is straightforward. It is to bolster the validity of the proposed media naturalness measurement scale and the related concepts by using them in an empirical study in the context of previously supported empirical findings.

Confirmatory Hypotheses

Mayfield and Mayfield report that "Above all, job satisfaction has been studied more than any other Motivating Language outcomes, but the correlation seems to be bimodal: either around 0.35 or around 0.65. Combined, these studies yield an r of about 0.35." (J. Mayfield & Mayfield, 2018, p. 76). This view leads to the following hypothesis:

Hypothesis 1: Motivating language is positively associated with job satisfaction.

Mayfield and Mayfield mention that "Studies have shown a relatively high relationship between leader motivating language use and follower organizational commitment" (J. Mayfield & Mayfield, 2018, p. 82). In their report of four studies, the values of the relationships range from 0.24 to 0.57 (J. Mayfield & Mayfield, 2018). These values lead to the following hypothesis:

Hypothesis 2: Motivating language is positively associated with organizational commitment.

As mentioned in the literature review section, job satisfaction and job performance, with various studies empirically finding linkages both directly and indirectly (Moqbel, 2012; Rehman, 2011; Rehman & Waheed, 2011; Zhang & Zheng, 2009). Thus, Hypothesis 3 is:

Hypothesis 3: Jobs satisfaction is positively associated with job performance.

The interest in the research on organizational commitment has stemmed from the presupposition that it influences work-related outcomes (J. Mayfield & Mayfield, 2018; Porter et al., 1974). This presupposition is reflected in the seemingly general consensus in the literature that an association exists between organizational commitment and job performance (Riketta, 2002), as well as in empirical support (Zhang & Zheng, 2009). This association leads to the following hypothesis:

Hypothesis 4: Organizational commitment is positively associated with job performance.

Exploratory Hypotheses

As was mentioned in previous sections of this study, motivating language's approach of broadening the scope of communication in the organization is a recent development. Indeed, MLT was proposed in "times when motivational theorists had their focus on uncertainty reducing managerial speech acts," (Gutierrez-Wirsching et al., 2015, p. 1239). On this topic, Mayfield and Mayfield mention that "Many predominant leadership theories marginalize spoken communication and take their cues from the Ohio State and University of Michigan studies, which are constructed around two leadership functions, task and people orientations." They also mention that "a lot of managerial talk relies on task orientation, a more narrow spectrum of spoken language that sets goals and outlines task expectations rather than enhancing employee motivation" (J. Mayfield & Mayfield, 2018, p. 18). On the other hand, motivating language strongly focuses "on the strategic use of leader language" (Holmes & Parker, 2017, p. 70). As was argued earlier in the study, these studies can be seen as focusing on task related orientation (Yunker & Hunt, 1976).

This study also emphasizes that MRT (Daft & Lengel, 1986; Daft et al., 1987) was proposed at a time when the need-satisfaction paradigm (Salancik & Pfeffer, 1978), which

Sullivan also referred to as the need-deficiencies model (Sullivan, 1988), had been prevalent in the field of management for several decades (Salancik & Pfeffer, 1978). This study has up to this point implied, and now explicitly argues, that in much the same manner as a great majority of the theories in the fields of management and motivation, MRT and its derived theories are shackled by the narrow definition of communication that is implicit in the need-satisfaction paradigm espoused by the Michigan and Ohio State leadership studies.

In this vein, this study further argues that in order to conduct a CMC study of a communication theory that has purposefully moved beyond the constraints of the need-deficiencies model, such as MLT, the theoretical perspective of CMC must similarly be free of said constraints. Such is the case for the media naturalness theory. It is not inconceivable that such a mismatch of underlying theoretical boundaries could be one of the challenges faced in the past when attempting integrate the rational choice and social theories in the field of CMC (Kock, 2004).

As mentioned earlier, the importance of speech in MLT is paramount. It is a constant theme in the literature. In his seminal article, Sullivan bases his theory on psycholinguistics and speech act theory and proposes that managerial communication can be categorized into speech acts (Sullivan, 1988). J. Mayfield et al. (1995) identify the "spoken language of leadership" as being of critical influence to worker outcomes when they present their original measurement instrument for motivating language. In a similar fashion, J. Mayfield et al. (1998) mention that "deliberate variance in leader *speech* can be used as a motivational tool" (J. Mayfield et al., 1998) (p. 236).

Talk is a vital component, since for most leaders, it can account for 60%-80% of their time (Holmes, 2012; J. Mayfield & Mayfield, 2018). The dimensions of motivating language make it clear that communication is more than words; how the message is delivered is also important (Holmes & Parker, 2017; J. Mayfield & Mayfield, 2018). When we couple this with, for example, the purpose of motivating language's dimension of empathetic language as reaffirming a follower's sense of self-worth as a human being through the use of emotional and humanistic language, it is not unreasonable to rationalize that a supervisor or manager may resort to a more natural form of communication when using motivating language, or that a follower may perceive a difference between more natural and less natural communications.

The aforementioned importance of speech and the strategic use of nuanced speech mentioned above also leads to the following question: When supervisors or leaders use less natural language does it affect the outcomes that motivating language is associated with? This question leads to the following hypotheses:

Hypothesis 5: Motivating language's effect on job satisfaction is moderated by media naturalness.

Hypothesis 6: Motivating language's effect on organizational commitment is moderated by media naturalness.

Hypothesis 7: The use of motivating language is positively associated with media naturalness.

CHAPTER IV

MEDIA NATURALNESS SCALE DEVELOPMENT

Items Measured on the Media Naturalness Scale

According to MNT's media naturalness proposition, the degree of naturalness of a communication medium can be assessed according to the degree in which it incorporates the five key elements of face-to-face communication: (a) colocation, which allows people to have the same context as well as see and hear each other; (b) synchronicity, which allows for rapid response; (c) the ability to observe and convey facial expressions; (d) the ability to observe and convey body language; and (e) the ability to convey and listen to speech. Additionally, the speech imperative proposition states that a medium's ability to convey and listen to speech is significantly more important than all of the other elements (Kock, 2004). Kock's evolutionary arguments for these elements of media naturalness and this proposition have been sufficiently discussed in Chapter 2 of this study. Therefore, while the proposed media naturalness scale (MNS) must include the use of these five key elements, it must also give more importance to the ability to convey and listen to speech.

The third proposition specified in the psychobiological model is the cognitive adaptation proposition. As mentioned in the literature review section of this study, the themes of this proposition are human learning, the plasticity of the human brain, and the role of specialized brain circuits in helping humans adapt to less natural forms of CMC media so that the cognitive effort is lower (Kock, 2004). A closely related concept in the compensatory adaptation theory proposed by Kock (Kock, 2001b, 2005a), which although can be seen as a precursor of MNT's cognitive adaptation proposition but has a different focus. Kock conducted a study of 12 process improvement groups that use e-communication whose findings were in direct contradiction to

MRT: he found a positive effect for process improvement, which he explained with the compensatory adaptation and social influence models (Kock, 2001b). Kock state: “The studies suggest that better outcomes are possible with the use of ‘lean’ media like email as group members adapt their behavior toward technology in a ‘compensatory’ way. The compensatory adaptation model argues that, if group members are motivated enough to accomplish their goals regarding a group task, they will overcompensate for the obstacles posed by media of low richness (according to the media richness classification proposed by media richness theory).” (Kock, 2001b, p. 270)

Subsequent studies have found support for the concept of compensatory adaptation. In his analysis of 20 business process redesign dyads, Kock (2005a) found that although the use of CMC increased cognitive effort and communication ambiguity, it did not affect the outcome of the task. The previous negative effects appeared to be counteracted by compensatory adaptation as evidenced by decreased fluency, and the use of message preparation. This mechanism of compensatory adaptation was validated in a subsequent empirical study involving 230 students using web-based quasi-synchronous CMC. The study found that the information givers experienced an increase in compensatory encoding of their messages while the receiver’s perceived effort in compensatory decoding was negligible. Thus, the study’s conclusion was that the burden of compensatory behavior falls on the sender (Kock, 2007).

The review of these findings serves to illustrate how the characteristics of the CMC medium facilitate cognitive adaptation behavior, as decreased synchronicity allowed more time for message preparation and therefore improved message encoding. Cognitive adaptation behavior will be referred to from now on as compensatory adaptation. Therefore, in order to be consistent with MNT’s cognitive adaptation proposition, the proposed MNS must take into account the characteristics of the CMC media that facilitate compensatory adaptation.

The fourth proposition of MNT is the schema alignment proposition. Kock argues that our ability to “store” mental schemas “is the main evolutionary ‘trick’ that allowed us to develop tools and processes” (Kock, 2004, p. 336). In the process of proposing MNT, Kock posits this proposition with enough latitude for it to be operationalized at different levels of abstraction and for different uses (Kock, 2004). It can conceivably be used to analyze schema alignment when comparing national cultures, organizational cultures, or even specific knowledge domains. This wide latitude and wide variety of applications makes it at once flexible and challenging: because it can be applied to different studies in a different manner there may in fact be several different operationalizations of this proposition that go beyond the scope of this study. Because this study uses two separate samples from individual countries, its focus is not on the communication between subjects of different cultures and is not domain-specific. Thus, the implementation of the schema alignment proposition will not be addressed in this study.

The future relevance of the Media Naturalness Scale

In order for the MNS to remain relevant for future research, it should first of all take into account the way in which people use different CMC media. This first point is addressed by the introduction of what has been labeled as a “communication stream” in previous chapters of this study. A communication stream is defined as the communication or conversation that takes place between two or more parties regarding a certain topic or subject. For example, a supervisor may communicate and clarify the issue of salary, commissions, bonuses, and benefits over a period of time by using different media. While the information regarding these topics should be given to the employee during the hiring process, it would not be unusual for further questions or clarifications to arise. A similar situation could occur regarding the employee’s roles and responsibilities. These two parallel conversations could conceivably happen over time on a variety of different communication media. These are examples of two different communication streams in one employee-supervisor dyad. It is also conceivable that because of the distinct nature of the two communication streams, a different mix of communication media could be used: maybe the supervisor feels that explaining roles and responsibilities requires more face-to-face explanations, while an email may be better suited to clarify a commission structure.

In this manner it is possible to compare CMC media in two different ways. The first is the traditional approach of conducting an empirical study comparing two or more communication media side by side. For example, email versus face-to-face or versus a more natural CMC platform, where the degree of naturalness is easily comparable. The second approach, which will be used in this study, is the use of a communication stream. This approach recognizes that in today's world people are likely to communicate via a variety of different CMC media, and takes that into account. By taking into account what CMC media are used in the course of communicating with someone, a naturalness score can be assigned to the entire communication stream. This approach will be explained in more detail later in the study.

Second, the MNS should be robust to the evolution and inclusion of new features in communication and collaboration platforms as well as (ideally) the evolution of completely new forms of CMC. This second point is addressed from two perspectives: the basis of scoring and the level of abstraction of CMC media. The basis of scoring is addressed in great part by the MNT itself. Since the theory is based on the features of the biological communication apparatus and not on the actual or perceived characteristics of a communication medium, there is a theoretically sound and arguably objective baseline measurement: the media naturalness score of face-to-face communication. Thus, the naturalness score of a new CMC medium is easily comparable to that of previously established CMC media.

In specifying the level of abstraction of the CMC media, this study makes a clear distinction between communication media and a communication platform: A communication platform is an aggregation of one or more communication media. It is the communication media for which the MNS is calculated. One example of a platform is cellular phone service: it is the integration of phone call and text message media. In this manner, the MNS is by definition unaffected by the addition of features to communication platforms.

For example, a video conference is a CMC medium that can be included in the Skype, Facebook Messenger, or WhatsApp platforms. Instant messaging is another such CMC medium that can include communications through various platforms such as Facebook Messenger, WhatsApp, Yammer, or Slack, or chat systems built into task management platforms for example. The cases of Facebook messenger and WhatsApp are especially relevant, since they are good examples of instant messaging platforms that have gradually added voice calling and video calling (Gerber, 2017; Rauv, 2017).

By making this distinction between a platform and the media that compose it, the use of the MNS in empirical research should be “forward comparable” with future research. To continue with the WhatsApp example, users of WhatsApp in an empirical survey may respond that they used instant messaging in 2009, voice calling in 2015, or video conferencing in 2018. The possible complications of comparing such empirical results can be avoided by using the MNS score as it is being constructed in this study.

How the Media Naturalness Score is Determined

As has been addressed in the literature review section of this study, MNT’s speech imperative proposition makes an evolutionary case of why speech is “significantly more important than the other elements in the expressive-perceptual dimension" (Kock, 2004, p. 335). This study takes this proposition as its cue to assign points to the different key elements of face-to-face communication as listed in MNT as a way of quantifying their relative importance in the context of face-to-face communication. This assignment was initially done via the following hypothetical scenario: in the course of a normal face-to-face conversation in the workplace, how important would you weigh the lack of element X, if it were to be removed? The speech imperative proposition manifests in this hypothetical scenario as the following restriction: no element can have more importance than speech. The result of this exercise is a ranking of the MNT's key elements of face-to-face communication from least important to most important with points being awarded according to the ranking: the most important feature will receive the most points, which is by definition speech. Facial expression is next in the list of priorities, synchronicity and body language are ranked equally in third place, and colocation is ranked in fourth place. As is evident form the table below, the assignment of points to the communication elements is in effect a reverse ranking. This approach tries to adhere to the MNT and minimize bias, and it is shown in Table 4.1.

Confirmatory Interviews

A series of interviews were conducted in order to attempt to find support for the above assignment of points to the communication elements. It is important to note at this point that these interviews are not meant to be of an exploratory nature, but rather confirmatory in the spirit of similar studies that support the MRT (Russ et al., 1990; Trevino, 1990) or do not (Fulk & Ryu, 1990) in the form of rankings.

These interviews were conducted either in person or via telephone. The people in question were given a written brief summary of MNT via email, and a meeting was scheduled about a day after they had read the material. They were then asked if there were any items that needed clarification. The item that surfaced most often was the speech imperative proposition that some interviewees founds overly restrictive. The interviewees were then asked to follow the hypothetical scenario described above within the situational and theoretical boundaries that follow. The situation boundary was worded along the lines of “You are in a typical face-to-face communication scenario at work.” The theoretical boundaries were drawn according to MNT and were as follows: Based on a perspective of evolutionary history, humans have evolved to communicate face-to-face. MNT argues that the most important feature of face-to-face communication is the ability to convey speech, as evidenced by the evolutionarily expensive placement of the larynx. This is followed by the ability to convey facial expressions, as evidenced by the unusually complex web of facial muscles that humans have. Consistent with the hypothetical scenario described above, they were asked, “If feature X was to be removed from a face-to-face conversation, how would it affect your ability to communicate? Provide a score of 4 for the most important and a score of 1 for the least. There must be at least 1 item scored with a 4, and 1 item scored with a 1.” This last restriction was placed in an effort to force the analysis of differentiation. The characteristics of the interviewees are listed on Table 4.2. The results are shown in Table 4.3.

Table 4.1: Proposed ranking and points of communication elements

Communication Element	Rank (from most to least important)	Points
Speech	1	4
Facial Expressions	2	3
Body Language	3	2
Synchronicity	3	2
Colocation	4	1

Table 4.2: Details of the interviewees

Subject	Sex	Job Description
1	F	Partner in a large business litigation practice
2	M	CIO of an educational institution
3	F	Principal at an inner-city, model school
4	M	Product line manager in the life sciences division of a multinational firm
5	M	Customer service manager at an insurance firm
6	M	Risk assessment manager at a financial services firm
7	F	Teacher at a K-12 institution with a Master's in Counseling

Table 4.3: Points assigned to the communication elements by interviewees

Person	Speech	Facial Exp	Synchronicity	Colocation	Body L.
1	4	2	1	2	3
2	3	4	3	1	2
3	3	2	1	2	4
4	4	3	2	1	2
5	4	3	2	1	3
6	4	3	2	1	2
7	4	3	1	2	2
Mean	3.71	2.85	1.71	1.42	2.57
Median	4	3	2	1	2
Mode	4	3	1	1	2
This Study	4	3	2	1	2

While some of the differences in the assignation of points are minor, some responses were quite different from the scores that were predicted by this study and are therefore worthy of mention. Subject number one, while conceding that the theoretical argument for the importance of facial expressions was valid, stated that body language was more important, since clients and other people in her line of work do not always verbalize everything. In her own words, "When I am talking to you, I am analyzing your body language. Your posture, the position of your arms. Your tension. It tells me a lot." Subject number three went further in that direction, disregarding the core precept of MNT contained in the speech imperative proposition. She said that when meeting with staff, but especially parents, the adequate reading of body language is crucial. In the personal interview I had with her, she stood up in her office and gestured while she said, “I have to be ready for anything. I need to assess where a situation is headed and be able to get ahead of it. Things can change direction very quickly.” The gestures and body language that she used to emphasize this was a standing posture of alertness, while constantly surveilling her surroundings and keeping an eye on both doors to her office. Interviewee number two was less specific on the reason behind placing more importance on facial expression than speech but kept emphasizing that to him it was really important. The people interviewed have a varied ethnical background, and while the cultural background may be somewhat varied because of this, it does not seem unreasonable to argue that it is no more varied than what one would expect to find in the United States.

With this system of points, it is now possible to arithmetically calculate a numerical degree of naturalness according to what face-to-face communication elements are supported by the communication medium, as seen on Table 4.4.

Table 4.4: Media Naturalness Score (MNS) for different communication media

	Speech	Facial E.	Body L.	Sync	Coloc.	Comp. Ad.	Score
Possible Pts	4	3	2	2	1	3	
Face-to-Face	4	3	2	2	1	0	12
Video Conf	4	3	0	2	0	0	9
Phone	4	0	0	2	0	0	6
Email	0	0	0	1	0	3	4
Social Media	0	0	0	1	0	3	4
Instant Messaging	0	0	0	1.5	0	2	3.5
Text Message	0	0	0	1	0	1	2
Written Instructions	0	0	0	0	0	3	3

At this point, some terminology clarifications are in order. First, as mentioned earlier in the chapter, this study does not consider a communication medium to be the same as a communication platform. A medium here is defined as a form of communication. To continue with the example of WhatsApp and Facebook Messenger, these two are separate platforms that allow users to communicate by using several forms of CMC media: voice calling, instant messaging, and video conferencing. Second, and related to the previous point, communication by social media platforms is restricted to posts, such as posting something on a Facebook page, and not the use of Facebook Messenger. Third, although the focus of this study is CMC, phone calls and written documents are included, with no distinction being made between physical documents and electronic documents. Phone calls and voice calls are the same CMC medium in this study; phone calls are considered voice calls on a different platform. As mentioned previously, the advantage of defining communication media in this manner is that studies remain robust and comparable in the face of constant technological evolution and the addition of features (or CMC media as they are referred to in this study) to different collaboration or communication platforms.

This study has defined a communication stream as a topic-specific conversation that may happen over a variety of communication media, and possibly over a certain period of time. In the context of this study, this stream translates into conversations on the topic of motivating language. For example, the first item in the measurement instrument for motivating language is regarding the direction giving language (DGL) dimension. When asking the respondent about communication from the boss, the statement reads: "Gives me useful explanations of what needs to be done in my work" (J. Mayfield et al., 1995, p. 443). This is the first of 10 indicators of this dimension of motivating language (J. Mayfield et al., 1995). Whether it is this particular statement, or the dimension of DGL (constituted by 10 different, but related statements) that constitutes the communication stream is a question of the level of abstraction and methodological perspective of the study that is being performed and will be discussed in Chapter V. For the time being, this single item is treated as an instance of a communication stream, and its degree of naturalness is calculated accordingly. In order to do so, the relative frequency of use of each communication medium must be established for the communication stream. In this particular case, the measurement item for motivating language can be adapted to measure the naturalness of its related communication stream and can look something like the sample question in Table 4.5.

Table 4.5: Sample item to measure naturalness of a communication stream

1=Very Little, 2=Little, 3=Some, 4=A lot, 5=A Whole Lot	Face-to-Face	Video Conf	Phone	email	Written Documents	Instant Messg	Text message	Social Media
When my boss gives me useful explanations of what needs to be done in my work, he/she uses	5	0	2	3	0	0	3	0

Based on this, a naturalness score can be calculated for the communication stream where the relative weights of the media represent their frequency of use that can be used to arrive at a communication naturalness score (CNS) as in Table 4.6.

The advantage of implementing the CNS in this manner is, as we will later see, that both the moderating effect of the media naturalness on motivating language can be specified as second-order latent variables, which is theoretically consistent with MLT (J. Mayfield et al., 1995, 1998).

Table 4.6: Determination of the Communication Naturalness Score (CNS)

Medium	Frequency	Weight	Medium Score	Total Points	
Face-to-Face	5	0.3125	12	3.75	
Video Conference	0	0	0	0	
Phone Call	2	0.125	6	0.75	
Email	3	0.1875	4	0.75	
Written Instructions	0	0	0	0	
Instant Message	0	0	0	0	
Text Message	3	0.1875	1	0.1875	
Social Media	3	0.1875	4	0.75	
Totals	16	1	27	6.1875	CNS

CHAPTER V

MODELS AND MEASURES

Research Stages

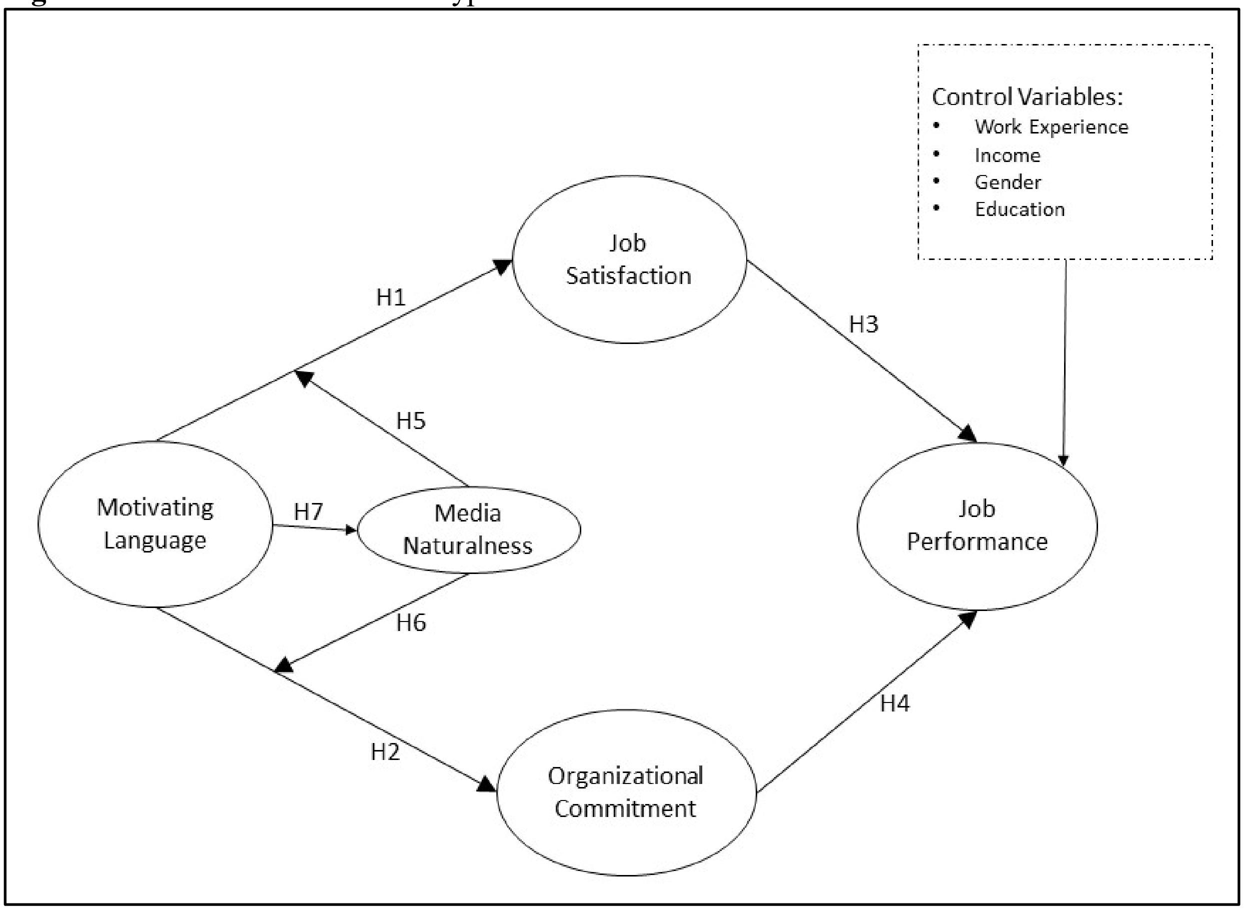
As has been previously stated, the purpose of this study is to develop and test a measurement scale for MN by applying it to empirical research. Due to the large exploratory nature of the project, it includes a pilot study and a main study that are both addressed in detail. It is the inclusion of these two phases of the study that makes the methodology section unusually extensive. Therefore, I have divided it into stages that are covered in the following paragraphs.

First, the research model and hypotheses will be presented. These will be used in both the pilot and the main study with the expectation that the main study will support the findings of the pilot study. The second stage will be the presentation of the measures that are used in the study. Both of these stages are covered in the present chapter. The third stage will be the presentation of the pilot study in Chapter VI, where topics such as data collection and preparation, model assessment, and results are covered. Chapter VII will cover the presentation of the principal study and its findings. It will cover the data collection and preparation, cultural manipulation checks and partial least squares, and model assessment (that includes the validity checks for the measurement and structural models). Chapter VII will also present the results and analyze them in detail. The topics of total, direct, and indirect effects will be covered as well as a multigroup analysis and measurement invariance analysis. Chapter VIII presents a discussion of the findings, as well as discussing some of the differences between the pilot and main studies. Finally, Chapter IX addresses the limitations and implications for future areas of research in the study.

Research Model and Hypotheses

The hypotheses presented previously are represented by the research model in Figure 5.1, and are summarized in Table 5.1.

Figure 5.1. Research Model and Hypotheses



Measures

The variables in the study were operationalized as latent variables. This approach is particularly advantageous for this study, since the implementation of a partial least squares and structural equation model will not only tend to minimize measurement error from these perception-based questions and reducing the collinearity among the latent variables (Schumacker & Lomax, 2004) but will also provide the necessary tools to assess the measurement model of the newly created media naturalness score with various samples and subsamples (Hair, Ringle, & Sarstedt, 2011; Kock, 2017).

Table 5.1: Hypotheses Summary

Hypothesis 1:	Motivating language is positively associated with job satisfaction.
Hypothesis 2:	Motivating language is positively associated with organizational commitment.
Hypothesis 3:	Job satisfaction is positively associated with job performance.
Hypothesis 4:	Organizational commitment is positively associated with job performance.
Hypothesis 5:	The association between motivating language and job satisfaction is moderated by media naturalness used to communicate said language.
Hypothesis 6:	The association between motivating language and organizational commitment is moderated by the media naturalness used to communicate said language.
Hypothesis 7:	The use of motivating language is positively associated with media naturalness.

Job satisfaction is measured with a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree based on Rehman (2011) and Rehman (2011) as used by Moqbel (2012). A sample indicator from the measurement scale is: “My present job gives me internal satisfaction.”.

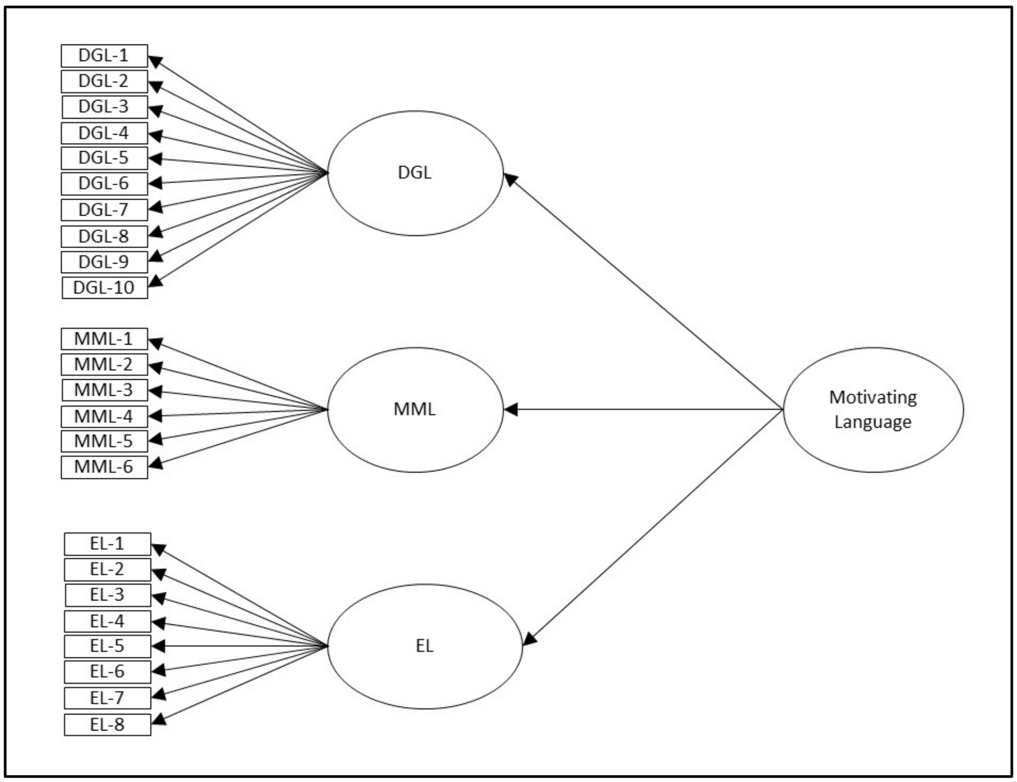
Organizational Commitment is measured on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree based on (Mowday, Porter, & Steers, 1982) in a fashion similar to that of previous studies (Moqbel, 2012). A sample indicator from the measurement scale is: “I am very pleased with my current job.”

Job performance is measured on a nine-item scale developed by J. Mayfield and Mayfield (2006). A sample indicator from the measurement scale is: “How does your level of production quantity compare to that of your colleagues’ productivity levels?”. All items were measured on a five-point Likert scale ranging from 1 = Bad to 5 = Excellent.

Motivating language is measured with the 24-item motivating language scale developed by J. Mayfield et al. (1995). The scale is used under a Creative Commons Share-Alike by Attribution license according to the requirements specified by the authors (J. Mayfield & Mayfield, 2008). The first 10 items correspond to the measurement of DGL. An example of one of the items is: “My boss gives me useful explanations of what needs to be done in my work.” The next six items correspond to the measurement of empathetic language. An example of one of the items is: “My boss asks me about my professional well-being.” The last eight items in the scale correspond to the measurement of meaning-making language. An example of one such item is: “My boss tells me stories about people who are admired in my organization.” Each of the 24 items on the scale is measured on a five-point Likert scale with the choice being: Very Little, Little, Some, A Lot, A Whole Lot. As is evident by the nature of the motivating language scale, motivating language is a latent variable that has three components: DGL, empathetic language (EL), and meaning-making language (MML). In turn, each of these components are latent variables where DGL is measured with 10 indicators, while EL is measured with 6 indicators and MML is measured with 8 indicators. Therefore, motivating language (ML) is operationalized in this study as a second-order latent variable, while its three components are operationalized as first-order latent variables. These in turn become the indicators for the second-order latent variable. Figure 5.2 shows ML as a second-order latent variable, the three dimensions of language as first-order latent variables, and the indicators for all first-order latent variables.

Media naturalness will be measured according to the scale described in Chapter IV. As mentioned in the previous chapter, the identification of a communication stream is both a matter of perspective based on different levels of abstraction as well as methodological perspective. From the perspective of ML, a communication stream could conceptually be identified at either the indicator level, or its two levels of abstraction listed in the previous paragraph. From a methodological perspective, the question is: how does one measure the degree of naturalness that is used when ML is being communicated? The most straightforward answer is: by finding out what communication media is being used when ML is being communicated.

Figure 5.2: ML as a second-order latent variable, first-order latent variables and indicators



As was also reviewed in the previous chapter, this identification is done by adapting the ML indicators to measure the CNS of its related communication stream. An example of an ML indicator is shown in Table 5.2, and the example of its adaptation to measure the CNS of its communication stream is shown in Table 5.3.

Since ML is operationalized as a second-order latent variable, the CNS of its related communication stream is operationalized in the same manner, as shown in Figure 5.3. The moderating effect of media naturalness on ML is therefore the interaction of these two second-order latent variables.

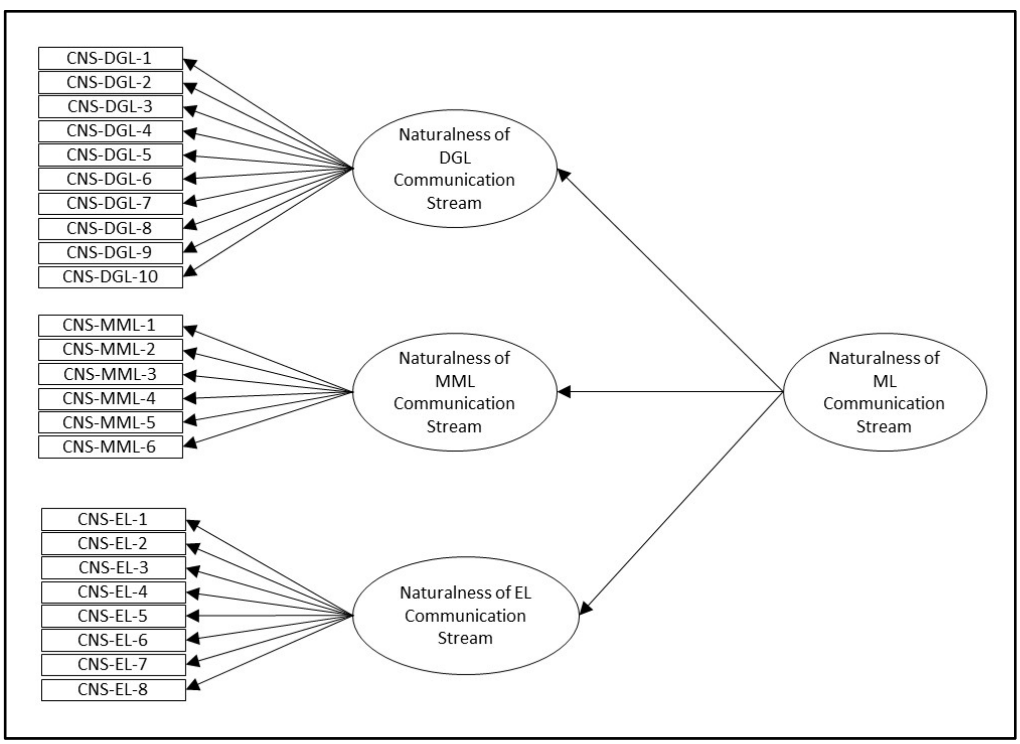
Table 5.2: Sample item to measure naturalness of a communication stream

My boss	**1=Very Little, 2=Little, 3=Some, 4=A lot, 5=A Whole Lot**
gives me useful explanations of what needs to be done in my work	3

Table 5.3: Sample item to measure naturalness of a communication stream

1=Very Little, 2=Little, 3=Some, 4=A lot, 5=A Whole Lot	Face-to Face	Video Conf	Phone	email	Written Documents	Instant Messg	Text message	Social Media
When my boss gives me useful explanations of what needs to be done in my work, he/she uses	5	0	2	3	0	0	3	0

Figure 5.3: Naturalness of the communication steam as a second-order latent variable, first-order latent variables and indicators



CHAPTER VI

PILOT STUDY

Data Collection

The study consists of a total of 105 collected surveys. Of these, 94 were collected by students that were enrolled in the researcher's various management information systems classes. The students were instructed on the proper way to fill out the survey. They were also instructed to find participants that were currently employed. They then proceeded to find these willing participants for the study and instructing them on the proper way to fill out the survey. They also assisted the participants in case questions arose related to the proper filling out of the survey. This form of student training was done in order to minimize missing information in the surveys. These surveys were collected over the course of two semesters, with 36 being collected in the fall of 2014 and 58 being collected in the spring of 2015. Additionally, 11 surveys were collected online in the spring of 2015. This was done by replicating the questionnaire as a Google form and distributing it online mainly through Facebook and LinkedIn.

Respondents that indicated part-time employment were discarded, since the research shows it is a moderating variable for ML (J. Mayfield & Mayfield, 2006).

Data Preparation

The first stage of data preparation was a missing data check. There were small amounts of demographic data missing where some respondents chose not to respond. Other data was not missing because the training that students received emphasized that the survey needed to be complete, and the online survey was configured so that complete answers were required.

Of the 94 surveys collected by students, 13 did not include age, 5 did not include gender, one did respondent chose not to reveal his education level, 9 chose not to reveal their ethnicity, and 58 did not disclose their managerial rank.

The second stage of data preparation was the calculation of the media naturalness score. This was done at the ML indicator level for each of the 21 indicators in the MLT measurement scale (J. Mayfield et al., 1995). Since ML is specified as a second-order latent variable (J. Mayfield et al., 1995), this was done with a spreadsheet software through a process that involved several distinct steps in order to adhere to the methodology detailed in the media naturalness section of Chapter IV.

Model Assessment

In the following sub-sections various forms of assessing the adequacy of the structural equation model.

Descriptive Statistics

Table 6.1 Presents the maximum and minimum values, and the median and mode for the latent variables in the model. Skewness and kurtosis coefficients are also reported, as well as the Jarque-Bera test of normality. The means are not presented, since WarpPLS normalizes the data of all the indicators before calculating the values of the latent variables. Further, three of the five variables (job satisfaction, job performance, and media naturalness) are not normally distributed in multivariate space, as indicated by their skewness and kurtosis coefficients as well as the Jarque-Bera test of normality.

The indicator correlation matrix for the second-order model is presented in stages for the sake of clarity.

Validity

The proposed model is evaluated using variance-based structural equation modeling (SEM), which is a powerful multivariate analysis technique that is frequently used for complex causal models such as this one (Chin, 1998). The advantage of partial least squares (PLS)-SEM versus covariance-based SEM is that the former uses non-parametric techniques such as resampling, so it implicitly makes no assumptions about the distribution of any of the variables involved or any of their indicators. This resampling makes it suitable for situations in which one or more of the criterion variables is not normally distributed (Hair et al., 2011; Siegel, 1956) as well as providing better accuracy and statistical power when smaller samples are used (Kock, 2015a; Kock & Hadaya, 2018).

A SEM comprises a measurement (outer) model structural model and a structural (inner) model (Kock, 2015a). The measurement model tests whether the latent variables in the model are sufficiently valid and reliable. This is done with a confirmatory factor analysis and various related techniques. The structural model is used to analyze the relation among the latent variables in the theoretical model (Chin, 1998; Kock, 2015a).

Table 6.1: Latent Variable Summary Statistics

	Job Satisfaction	Organizational Commitment	Job Performance	Motivating Language	Media Naturalness
Minimum Value	-2.905	-2.524	-4.976	-2.044	-2.66
Maximum Value	1.499	1.959	1.818	1.741	4.345
Median	0.175	0.02	0.108	0.145	-0.012
Mode	-2.905	-2.524	-4.976	-2.044	-2.66
Skewness Coefficient	-0.972	-0.315	-1.274	-0.338	0.406
Kurtosis Coefficient	0.492	-0.398	4.441	-0.906	2.317
Jarque-Bera test of Normality	No	Yes	No	Yes	No

Measurement Model

The validity and reliability of the measurement model's latent variables is assessed. The structure matrix of Pearson correlations between the indicators and latent variables was obtained through a confirmatory factor analysis that uses principal components as the means of extraction

(Chin, 1998) and subsequently transformed using oblique (Promax) rotation to obtain the cross-loadings (Kock, 2011, 2015a). This form of rotation is arguably better suited than orthogonal rotation in models where the correlations among latent variables is expected or theorized (Kline, 2005; Schumacker & Lomax, 2004). The loadings of the indicators to their corresponding latent variable are unrotated (Kock, 2015a).

A confirmatory factor analysis was made to ensure that the latent variables conform to the acceptable discriminant and convergent validity criteria. The criterion for convergent validity is that the indicators have a loading equal to or greater than 0.5 on their corresponding latent variable, while their cross-loadings should be less than 0.5 on all other latent variables (Hair, 1992; Kock, 2014). These loadings should be statistically significant at the 5% level ($P<0.05$) (Bagozzi & Yi, 1988; Fornell & Larcker, 1981). The loadings, cross-loadings, and statistical significance (P-values) for the latent variables of the first-order model are shown in Table 6.3, and those of the second-order model are shown in Table 6.4.

There were no items in the latent variables of either the first-order model or the second-order model that needed to be removed because of inadequate loading values (Kock, 2015a). All the factors loadings in both models are significant at the $P<0.001$ level with the exception of indicator JP1 on the second-order model, which is significant at the $P<0.05$ level. The loadings vary from 0.661 to 0.916 for the first-order model as can be seen on Table 6.3.

The loadings vary from 0.628 to 0.945 for the second-order model, as can be seen on Table 6.4. The loadings indicate that the measurement instrument has acceptable convergent validity (Hair et al., 2011; Kock, 2015a).

Discriminant validity was tested by comparing the inter-construct correlations with the square root of the average variance extracted (AVE) of each variable. Tables 6.5 and 6.6 show

Table 6.2: Indicator Correlation Matrix

	SAT1	SAT2	SAT3	SAT4	SAT5	COM1	COM2	COM3	COM4	COM5	JP1	JP2	JP3
SAT1	1.000												
SAT2	0.716	1.000											
SAT3	0.657	0.854	1.000										
SAT4	0.816	0.761	0.710	1.000									
SAT5	0.811	0.659	0.636	0.751	1.000								
COM1	0.552	0.602	0.530	0.608	0.550	1.000							
COM2	0.657	0.693	0.703	0.740	0.607	0.629	1.000						
COM3	0.467	0.486	0.492	0.601	0.412	0.498	0.769	1.000					
COM4	0.470	0.446	0.417	0.539	0.401	0.431	0.546	0.534	1.000				
COM5	0.430	0.325	0.370	0.460	0.383	0.306	0.493	0.632	0.696	1.000			
JP1	0.042	0.043	0.051	0.028	0.066	-0.053	-0.005	-0.065	-0.128	-0.120	1.000		
JP2	0.079	0.022	-0.019	0.104	0.133	-0.019	-0.005	0.114	0.083	0.092	0.069	1.000	
JP3	0.121	0.045	0.002	0.166	0.086	0.027	0.099	0.180	0.136	0.095	0.056	0.682	1.000
JP4	0.142	0.111	0.055	0.089	0.185	0.057	0.060	0.137	0.159	0.126	0.181	0.469	0.488
JP5	0.146	0.087	0.037	0.109	0.159	-0.029	0.071	0.122	0.250	0.147	0.166	0.450	0.443
JP6	0.084	0.088	0.048	0.125	0.042	0.035	0.189	0.210	0.168	0.090	0.164	0.466	0.494
JP7	0.147	0.059	0.167	0.072	0.160	-0.065	0.113	0.105	0.154	0.158	0.028	0.403	0.285
JP8	0.128	0.055	0.132	0.105	0.144	0.017	0.149	0.203	0.161	0.224	0.032	0.510	0.419
JP9	0.121	0.144	0.171	0.156	0.052	0.096	0.174	0.151	0.160	0.043	0.168	0.362	0.327
LD	0.465	0.415	0.339	0.410	0.439	0.245	0.428	0.410	0.280	0.312	0.076	0.146	0.227
LE	0.370	0.377	0.307	0.353	0.416	0.223	0.398	0.345	0.271	0.289	0.004	0.169	0.266
LM	0.309	0.341	0.326	0.374	0.337	0.224	0.441	0.429	0.419	0.415	-0.012	0.116	0.249
MD	0.195	0.144	0.073	0.094	0.249	0.006	0.064	0.018	0.143	0.106	-0.002	0.027	0.052
ME	0.135	0.123	0.072	0.060	0.190	0.029	0.033	0.060	0.177	0.159	-0.016	0.027	0.050
MM	0.189	0.127	0.064	0.087	0.291	0.033	0.054	0.060	0.183	0.211	0.032	0.050	-0.004

Table 6.2: Indicator Correlation Matrix Measurement Model (Continued)

	JP4	JP5	JP6	JP7	JP8	JP9	ML-D	ML-E	ML-M	MN-D	MN-E	MN-M
JP4	1.000											
JP5	0.586	1.000										
JP6	0.480	0.603	1.000									
JP7	0.485	0.498	0.529	1.000								
JP8	0.472	0.505	0.399	0.537	1.000							
JP9	0.441	0.483	0.518	0.449	0.543	1.000						
LD	0.248	0.254	0.262	0.264	0.200	0.160	1.000					
LE	0.265	0.290	0.324	0.318	0.201	0.148	0.831	1.000				
LM	0.188	0.202	0.214	0.214	0.197	0.146	0.808	0.757	1.000			
MD	0.108	0.195	0.103	0.165	0.008	-0.049	0.415	0.360	0.301	1.000		
ME	0.112	0.133	0.024	0.063	-0.034	-0.068	0.361	0.303	0.261	0.820	1.000	
MM	0.110	0.136	0.003	0.109	0.010	-0.136	0.429	0.330	0.353	0.742	0.777	1.000

the square root of the AVEs for the variables shaded in the diagonal, and the inter-construct correlations for the first-order and second-order models, respectively. When comparing the square root of the AVEs, with the other values in the column (correlations), the square root of the

Table 6.3: Loadings and cross-loadings for the first-order model

	LD	LE	LM	MD	ME	MM	Type	SE	P value
LD1	**0.862**	-0.042	-0.256	-0.173	0.033	0.125	Reflective	0.078	<0.001
LD2	**0.892**	0.151	-0.196	-0.067	-0.019	0.139	Reflective	0.077	<0.001
LD3	**0.851**	0.223	-0.222	0.023	-0.15	0.223	Reflective	0.078	<0.001
LD4	**0.904**	-0.108	-0.015	-0.065	0.052	-0.007	Reflective	0.077	<0.001
LD5	**0.839**	-0.203	0.29	-0.029	0.026	-0.02	Reflective	0.078	<0.001
LD6	**0.88**	-0.228	0.088	-0.002	-0.004	-0.026	Reflective	0.077	<0.001
LD7	**0.79**	0.103	-0.026	0.08	0.126	-0.298	Reflective	0.079	<0.001
LD8	**0.83**	-0.068	0.033	-0.01	0.169	-0.164	Reflective	0.078	<0.001
LD9	**0.818**	-0.061	0.129	-0.043	-0.116	0.179	Reflective	0.079	<0.001
LD10	**0.809**	0.254	0.203	0.315	-0.116	-0.187	Reflective	0.079	<0.001
LE1	0.198	**0.904**	-0.215	-0.09	0.035	0.1	Reflective	0.077	<0.001
LE2	0.261	**0.916**	-0.127	0.01	0.082	-0.125	Reflective	0.077	<0.001
LE3	0.013	**0.906**	0.136	-0.014	-0.097	0.121	Reflective	0.077	<0.001
LE4	-0.292	**0.885**	0.219	0.033	-0.001	-0.081	Reflective	0.077	<0.001
LE5	-0.157	**0.912**	0.122	0.114	-0.136	0.029	Reflective	0.077	<0.001
LE6	-0.043	**0.661**	-0.178	-0.073	0.162	-0.061	Reflective	0.082	<0.001
LM1	0.269	0.019	**0.799**	0.174	-0.038	0.003	Reflective	0.079	<0.001
LM2	0.034	0.326	**0.84**	-0.008	0.07	-0.038	Reflective	0.078	<0.001
LM3	0.024	0.075	**0.905**	-0.1	-0.01	0.015	Reflective	0.077	<0.001
LM4	-0.042	0.029	**0.88**	0.122	-0.049	-0.097	Reflective	0.077	<0.001
LM5	0.02	-0.084	**0.807**	-0.032	-0.109	0.147	Reflective	0.079	<0.001
LM6	0.026	-0.225	**0.865**	-0.099	0.031	0.05	Reflective	0.078	<0.001
LM7	-0.038	0.006	**0.886**	0.046	0.027	-0.1	Reflective	0.077	<0.001
LM8	-0.297	-0.16	**0.782**	-0.099	0.079	0.034	Reflective	0.079	<0.001
MD1	-0.095	0.217	-0.154	**0.719**	-0.566	0.176	Reflective	0.081	<0.001
MD2	-0.086	0.135	-0.065	**0.896**	-0.241	-0.022	Reflective	0.077	<0.001
MD3	0.089	-0.031	-0.022	**0.824**	0.369	-0.44	Reflective	0.078	<0.001
MD4	-0.201	0.259	-0.208	**0.796**	-0.054	0.338	Reflective	0.079	<0.001
MD5	-0.307	0.336	-0.022	**0.848**	-0.089	0.284	Reflective	0.078	<0.001
MD6	-0.053	0.052	0.061	**0.868**	0.219	-0.024	Reflective	0.078	<0.001
MD7	0.128	-0.071	0.084	**0.698**	0.515	-0.466	Reflective	0.081	<0.001
MD8	0.199	-0.242	0.107	**0.846**	-0.101	-0.135	Reflective	0.078	<0.001
MD9	0.147	-0.296	0.055	**0.718**	-0.153	0.115	Reflective	0.081	<0.001
MD10	0.222	-0.408	0.165	**0.786**	0.105	0.158	Reflective	0.079	<0.001
ME1	-0.115	0.141	0.046	-0.038	**0.904**	-0.096	Reflective	0.077	<0.001
ME2	0.204	-0.189	-0.028	0.105	**0.894**	-0.305	Reflective	0.077	<0.001
ME3	-0.041	-0.096	0.168	-0.034	**0.876**	0.073	Reflective	0.077	<0.001
ME4	0.074	-0.059	0.027	-0.027	**0.909**	0.052	Reflective	0.077	<0.001
ME5	-0.011	0.046	-0.056	-0.147	**0.899**	0.057	Reflective	0.077	<0.001
ME6	-0.115	0.158	-0.157	0.145	**0.873**	0.226	Reflective	0.077	<0.001
MM1	-0.167	-0.002	0.164	0.28	0.018	**0.862**	Reflective	0.078	<0.001
MM2	0.095	0.085	-0.221	0.101	0.327	**0.775**	Reflective	0.079	<0.001
MM3	-0.183	0.203	0.061	0.018	-0.143	**0.854**	Reflective	0.078	<0.001
MM4	-0.073	0.23	-0.12	0.454	-0.302	**0.782**	Reflective	0.079	<0.001
MM5	0.33	-0.273	-0.135	-0.282	-0.031	**0.687**	Reflective	0.081	<0.001
MM6	0.336	-0.368	0.028	-0.363	0.059	**0.781**	Reflective	0.079	<0.001
MM8	-0.257	0.073	0.178	-0.266	0.081	**0.8**	Reflective	0.079	<0.001

Notes: First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning-making dimension. Thus LM8 is the score of motivating language's meaning-making indicator 8, and MM8 is the media naturalness score for the indicator. Loadings are shaded grey and cross loadings are not shaded.

AVE should be greater than all the correlations in the column. Since the above conditions were met, the results of this test indicate that the discriminant validity of the latent variables is satisfactory for both models (Fornell & Larcker, 1981; Kock, 2015a).

Table 6.4: Loadings and cross loadings for second-order model

	ML	MN	SAT	JP	OC	MN*ML	Type (a	SE	P value
LD	**0.945**	0.033	0.046	-0.012	-0.108	-0.044	Formative	0.076	<0.001
LE	**0.877**	-0.041	-0.054	0.032	-0.056	-0.035	Formative	0.077	<0.001
LM	**0.87**	-0.064	-0.257	-0.053	0.247	-0.014	Formative	0.077	<0.001
MD	0.104	**0.881**	0.057	0.072	-0.187	0.17	Formative	0.077	<0.001
ME	-0.022	**0.907**	-0.125	-0.042	0.103	0.044	Formative	0.077	<0.001
MM	-0.011	**0.873**	-0.022	-0.028	0.064	-0.131	Formative	0.077	<0.001
SAT1	-0.045	0.054	**0.89**	0.086	-0.191	0.018	Formative	0.077	<0.001
SAT2	-0.009	-0.025	**0.872**	0.014	-0.201	0	Formative	0.077	<0.001
SAT3	-0.055	-0.099	**0.834**	0	-0.101	-0.029	Formative	0.078	<0.001
SAT4	-0.102	-0.098	**0.898**	0.074	0.051	-0.04	Formative	0.077	<0.001
SAT5	-0.046	0.125	**0.833**	0.07	-0.249	-0.07	Formative	0.078	<0.001
JP1	0.133	-0.116	0.232	**0.663**	-0.972	-0.057	Formative	0.093	0.042
JP2	-0.253	-0.061	0.098	**0.684**	-0.063	-0.165	Formative	0.081	<0.001
JP3	0.049	-0.107	-0.106	**0.647**	0.072	-0.075	Formative	0.082	<0.001
JP4	0.014	0.09	0.121	**0.744**	-0.2	0.026	Formative	0.08	<0.001
JP5	-0.088	0.09	-0.039	**0.741**	0.009	-0.023	Formative	0.08	<0.001
JP6	0.116	-0.086	-0.237	**0.723**	0.168	-0.01	Formative	0.081	<0.001
JP7	0.05	0.079	-0.082	**0.687**	-0.005	0.148	Formative	0.081	<0.001
JP8	-0.173	-0.165	-0.102	**0.734**	0.285	-0.22	Formative	0.08	<0.001
JP9	0.007	-0.175	0.087	**0.653**	-0.039	0.059	Formative	0.082	<0.001
COM1	0.102	0.002	0.355	-0.272	**0.628**	0.005	Formative	0.083	<0.001
COM2	0.11	-0.178	0.38	-0.084	**0.83**	-0.033	Formative	0.078	<0.001
COM3	0.066	-0.203	-0.218	-0.075	**0.825**	-0.195	Formative	0.078	<0.001
COM4	-0.206	0.169	-0.159	0.093	**0.799**	0.104	Formative	0.079	<0.001
COM5	-0.142	0.086	-0.39	-0.014	**0.741**	-0.064	Formative	0.08	<0.001
MD*LD	-0.245	0.165	0.101	0.001	0.05	**0.862**	Formative	0.078	<0.001
MD*LE	-0.278	0.174	0.288	-0.011	-0.063	**0.864**	Formative	0.078	<0.001
MD*LM	-0.069	0.061	-0.093	-0.058	0.15	**0.827**	Formative	0.078	<0.001
ME*LD	-0.045	0.15	-0.088	-0.05	0.047	**0.903**	Formative	0.077	<0.001
ME*LE	-0.107	0.104	0.12	-0.022	-0.074	**0.902**	Formative	0.077	<0.001
ME*LM	0.092	-0.08	-0.108	0.005	0.014	**0.921**	Formative	0.076	<0.001
MM*LD	0.008	-0.071	-0.011	0.078	-0.046	**0.933**	Formative	0.076	<0.001
MM*LE	-0.031	-0.026	0.155	0.093	-0.183	**0.924**	Formative	0.076	<0.001
MM*LM	0.129	-0.141	-0.11	0.043	0.001	**0.899**	Formative	0.077	<0.001

Notes: First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning-making dimension. Thus, LM is the score of motivating language's meaning-making dimension, and MM is the is the degree of media naturalness used when communicating the meaning-making dimension. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*). Loadings are shaded grey and cross loadings are not shaded.

Measurement reliability has traditionally been assessed using composite reliability (CR) or Cronbach's alpha (CA) based tests. CA provides an estimate of the indicator intercorrelations (Henseler, Ringle, & Sinkovics), and an acceptable measure is 0.7 or higher (Nunnally &

Bernstein, 1994). Another measure of reliability is CR, which should have a score of 0.7 or greater in order for the measure to be reliable (Hair, 1992; Nunnally & Bernstein, 1994). The CR takes into account the score loadings unlike CA, thus its use is recommended when using PLS (Hair et al., 2011). A score of 0.7 or above is considered an indicator that a latent variable has acceptable reliability (Kock & Mayfield, 2015; Nunnally & Bernstein, 1994). Table 6.7 shows that the CRs are above threshold values in the first-order model, and Table 6.8 shows the same for the second-order model.

Table 6.5: Correlations between the latent variables and the square root of the AVEs for the first-order model

	LD	LE	LM	MD	ME	MM
LD	**0.848**					
LE	0.831	**0.869**				
LM	0.808	0.757	**0.847**			
MD	0.415	0.36	0.301	**0.803**		
ME	0.361	0.303	0.261	0.82	**0.892**	
MM	0.429	0.33	0.353	0.742	0.777	**0.793**

Notes: The square roots of the average variance extracted (AVEs) are shaded grey in the diagonal. The correlations among variables are not shaded. First Letter: “L” indicates a motivating language indicator; M indicates media naturalness that is being measured at the ML indicator. Second Letter: “D” indicates the direction giving dimension; “E” indicates the empathetic language dimension; “M” indicates the meaning-making dimension. Thus, LM is the score of motivating language’s meaning-making dimension, and MM is the degree of media naturalness used when communicating the meaning-making dimension.

A full collinearity test is also run in order to examine the existence of multicollinearity among the latent variables. This is done by calculating the variance inflation factors (VIFs) for each latent variable in relation to the rest of the latent variables in the model (Kline, 2005). The full collinearity VIFs are calculated automatically for all the variables by WarpPLS 6.0 (Kock, 2015a). The test for both models shows that there are no multicollinearity issues, since all the values are below the acceptable threshold of 5, as seen on Table 6.9 for the first-order model and Table 6.10 for the second-order model (Hair et al., 2011; Kline, 2005).

Table 6.6: Correlations between the latent variables and the square root of the AVEs for the second-order model

	ML	MN	SAT	JP	OC	EXP	AHI	ED	GDR	MN*ML
ML	**0.898**									
MN	0.413	**0.887**								
SAT	0.523	0.202	**0.866**							
JP	0.345	0.101	0.193	**0.664**						
OC	0.533	0.182	0.779	0.267	**0.768**					
EXP	-0.216	-0.212	-0.016	0.163	-0.074	**1**				
AHI	-0.188	-0.143	-0.027	0.037	-0.225	0.383	**1**			
ED	-0.174	-0.186	-0.02	0.012	-0.082	0.146	0.222	**1**		
GDR	-0.072	-0.163	-0.17	-0.162	-0.166	-0.106	0.067	0.071	**1**	
MN*ML	-0.27	-0.444	0.034	-0.066	0.08	0.181	0.018	0.119	0.034	**0.893**

Notes: The square roots of the average variance extracted (AVEs) are shaded grey in the diagonal. The correlations among variables are not shaded. ML = motivating language. MN = media naturalness. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*).

Table 6.7: Latent Variable Coefficients for the first-order model

	LD	LE	LM	MD	ME	MM
R-Squared						
Composite Reliability	0.962	0.948	0.953	0.947	0.959	0.922
Cronbach's alpha	0.956	0.933	0.943	0.937	0.949	0.901
Average Variance Extracted	0.719	0.755	0.717	0.644	0.796	0.63
Q-squared						

First Letter: "L" indicates a motivating language indicator; M indicates media naturalness that is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning m-making dimension. Thus, LM is the score of motivating language's meaning meaning-making dimension, and MM is the degree of media naturalness used when communicating the meaning meaning-making dimension.

Table 6.8: Latent Variable Coefficients for the second-order model

	ML	MN	SAT	JP	OC	MN*ML
R-Squared		0.194	0.307	0.214	0.338	
Composite Reliability	0.926	0.917	0.937	0.869	0.877	0.973
Cronbach's alpha	0.922	0.914	0.933	0.854	0.861	0.973
Average Variance Extracted	0.806	0.787	0.75	0.441	0.59	0.798
Q-squared		0.19	0.31	0.201	0.338	

ML = motivating language. MN = media naturalness. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*).

Table 6.9: Full collinearity Variance Inflation Factors for the first-order model

LD	4.582
LE	3.53
LM	3.159
MD	3.467
ME	3.811
MM	2.948

First Letter: “L” indicates a motivating language indicator; M indicates media naturalness that is being measured at the ML indicator. Second Letter: “D” indicates the direction giving dimension; “E” indicates the empathetic language dimension; “M” indicates the meaning m-making dimension. Thus, LM is the score of motivating language’s meaning meaning-making dimension, and MM is the degree of media naturalness used when communicating the meaning meaning-making dimension.

Table 6.10: Full collinearity Variance Inflation Factors for the first-order model

ML	2.049
MN	1.482
SAT	2.954
JP	1.273
OC	3.126
EXP	1.337
AHI	1.362
ED	1.101
GDR	1.11
MN*ML	1.385

ML = motivating language. MN = media naturalness. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*). EXP = experience, AHI = annual household income. ED = education. GDR = gender.

Table 6.11 shows the indicator weights for the first -order models as well as the standard error, P value, VIF, weight loading sign (WLS), and effect size (ES). Table 6.12 shows the indicator weights for the second-order models as well as the standard error, P value, VIF, weight loading sign (WLS), and effect size (ES). The WLS should have a value of one to indicate the absence of Simpson’s Paradox, and therefore possible model misspecification (Kock & Gaskins, 2016).

Ideally, the VIF values should be no greater than 2.5 for indicators of formative variables (Hair et al., 2011; Kock, 2015a), and values above this threshold indicate that the offending indicators need to be merged (Hair et al., 2011). However, doing this merger contradicts the theoretical foundations of motivating language theory. For this reason, we proceed with caution

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Table 6.11: Indicator weights for the first-order model

	LD	LE	LM	MD	ME	MM	Type	SE	P value	VIF	WLS	ES
LD1	0.120						Reflective	0.095	0.104	4.112	1	0.103
LD2	0.124						Reflective	0.094	0.096	4.770	1	0.111
LD3	0.118						Reflective	0.095	0.107	3.713	1	0.101
LD4	0.126						Reflective	0.094	0.093	5.857	1	0.114
LD5	0.117						Reflective	0.095	0.110	3.620	1	0.098
LD6	0.122						Reflective	0.094	0.099	4.411	1	0.108
LD7	0.110						Reflective	0.095	0.125	2.611	1	0.087
LD8	0.115						Reflective	0.095	0.113	3.458	1	0.096
LD9	0.114						Reflective	0.095	0.116	2.963	1	0.093
LD10	0.112						Reflective	0.095	0.119	2.498	1	0.091
LE1		0.200					Reflective	0.093	0.017	5.627	1	0.181
LE2		0.202					Reflective	0.092	0.016	5.888	1	0.185
LE3		0.200					Reflective	0.093	0.016	5.797	1	0.181
LE4		0.195					Reflective	0.093	0.019	4.267	1	0.173
LE5		0.201					Reflective	0.093	0.016	5.836	1	0.184
LE6		0.146					Reflective	0.094	0.061	1.779	1	0.097
LM1			0.139				Reflective	0.094	0.071	2.760	1	0.111
LM2			0.146				Reflective	0.094	0.061	3.507	1	0.123
LM3			0.158				Reflective	0.094	0.047	4.753	1	0.143
LM4			0.153				Reflective	0.094	0.052	3.908	1	0.135
LM5			0.141				Reflective	0.094	0.069	2.701	1	0.113
LM6			0.151				Reflective	0.094	0.055	3.890	1	0.130
LM7			0.155				Reflective	0.094	0.051	3.932	1	0.137
LM8			0.136				Reflective	0.094	0.075	2.599	1	0.107
MD1				0.112			Reflective	0.095	0.121	2.838	1	0.080
MD2				0.139			Reflective	0.094	0.071	8.260	1	0.125
MD3				0.128			Reflective	0.094	0.089	3.809	1	0.105
MD4				0.124			Reflective	0.094	0.097	4.909	1	0.098
MD5				0.132			Reflective	0.094	0.083	4.080	1	0.112
MD6				0.135			Reflective	0.094	0.078	5.695	1	0.117
MD7				0.108			Reflective	0.095	0.128	2.838	1	0.076
MD8				0.131			Reflective	0.094	0.083	3.767	1	0.111
MD9				0.111			Reflective	0.095	0.121	2.506	1	0.080
MD10				0.122			Reflective	0.094	0.100	2.938	1	0.096
ME1					0.189		Reflective	0.093	0.022	4.211	1	0.171
ME2					0.187		Reflective	0.093	0.023	3.926	1	0.167
ME3					0.183		Reflective	0.093	0.026	3.398	1	0.160
ME4					0.190		Reflective	0.093	0.021	4.255	1	0.173
ME5					0.188		Reflective	0.093	0.023	3.918	1	0.169
ME6					0.183		Reflective	0.093	0.026	3.244	1	0.159
MM1						0.196	Reflective	0.093	0.019	3.766	1	0.169
MM2						0.176	Reflective	0.093	0.031	2.380	1	0.136
MM3						0.194	Reflective	0.093	0.019	3.448	1	0.166
MM4						0.177	Reflective	0.093	0.030	2.407	1	0.139
MM5						0.156	Reflective	0.094	0.049	2.368	1	0.107
MM6						0.177	Reflective	0.093	0.030	2.964	1	0.139
MM8						0.181	Reflective	0.093	0.027	2.187	1	0.145

Structural Model

Model fit was evaluated using average path coefficients (APC), average R-squared

(ARS), and average variance inflation factor (AVIF). It is recommended that the first two should be at least 0.05, while the AVIF should be lower than 5 (Hair, 1992; Kline, 2005; Kock & Mayfield, 2015). Table 6.13 shows the results are acceptable according to the above criteria that means the data are good fits for the second-order model. Model fit indices are not reported for the first-order model, since it is used solely to convert the first-order latent variables LD, LE, LM, MD, ME, MM into usable indicators so that they can be used to create the second-order latent variables ML and MN.

Table 6.12: Indicator weights for the second-order model

	ML	MN	SAT	JP	OC	EXP	AHI	ED	GDR	MN*ML	Type	SE	P value	VIF	WLS	ES
LD	0.524										Formative	0.085	<0.001	4.270	1.000	0.496
LE	0.233										Formative	0.092	0.006	3.461	1.000	0.204
LM	0.220										Formative	0.092	0.009	3.094	1.000	0.191
MD		0.189									Formative	0.093	0.022	3.343	1.000	0.166
ME		0.379									Formative	0.088	<0.001	3.787	1.000	0.344
MM		0.415									Formative	0.087	<0.001	2.758	1.000	0.362
SAT1			0.266								Reflective	0.091	0.002	4.232	1.000	0.237
SAT2			0.277								Reflective	0.091	0.001	4.643	1.000	0.242
SAT3			0.122								Reflective	0.094	0.101	3.877	1.000	0.101
SAT4			0.258								Reflective	0.091	0.003	3.910	1.000	0.232
SAT5			0.153								Reflective	0.094	0.053	3.213	1.000	0.127
JP1				0.021							Reflective	0.097	0.416	1.082	1.000	0.003
JP2				0.159							Reflective	0.094	0.046	2.190	1.000	0.109
JP3				0.119							Reflective	0.095	0.106	2.184	1.000	0.077
JP4				0.175							Reflective	0.093	0.032	1.890	1.000	0.130
JP5				0.184							Reflective	0.093	0.025	2.083	1.000	0.136
JP6				0.182							Reflective	0.093	0.027	2.126	1.000	0.132
JP7				0.123							Reflective	0.094	0.098	1.848	1.000	0.085
JP8				0.181							Reflective	0.093	0.027	1.987	1.000	0.133
JP9				0.119							Reflective	0.095	0.106	1.742	1.000	0.077
COM1					0.075						Reflective	0.096	0.217	1.709	1.000	0.047
COM2					0.276						Reflective	0.091	0.001	3.165	1.000	0.229
COM3					0.331						Reflective	0.089	<0.001	3.104	1.000	0.273
COM4					0.265						Reflective	0.091	0.002	2.248	1.000	0.212
COM5					0.162						Reflective	0.093	0.043	2.465	1.000	0.120
EXP						1.000					Reflective	0.075	<0.001	0.000	1.000	1.000
AHI							1.000				Reflective	0.075	<0.001	0.000	1.000	1.000
ED								1.000			Reflective	0.075	<0.001	0.000	1.000	1.000
GDR									1.000		Reflective	0.075	<0.001	0.000	1.000	1.000
MD*LD										0.190	Reflective	0.093	0.022	25.715	1.000	0.164
MD*LE										0.087	Reflective	0.095	0.183	19.836	1.000	0.075
MD*LM										-0.048	Reflective	0.096	0.310	13.408	-1.000	0.040
ME*LD										-0.074	Reflective	0.096	0.221	36.826	-1.000	0.067
ME*LE										0.079	Reflective	0.096	0.205	44.325	1.000	0.071
ME*LM										0.369	Reflective	0.088	<0.001	16.398	1.000	0.340
MM*LD										0.217	Reflective	0.092	0.010	28.963	1.000	0.203
MM*LE										0.196	Reflective	0.093	0.018	23.122	1.000	0.181
MM*LM										0.030	Reflective	0.097	0.379	14.762	1.000	0.027

Table 6.13: Model fit indices for the second-order model

APC	ARS	AVIF
0.247, P=0.004	0.223, P=0.008	1.222

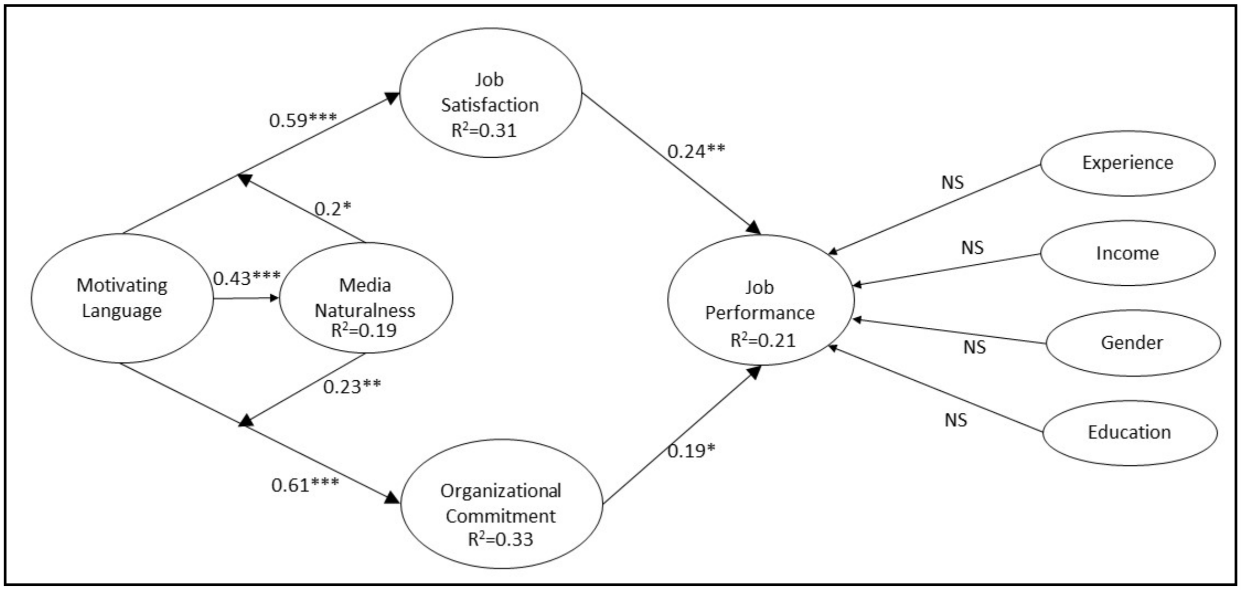
Results

The following sub-sections will cover the results of the pilot study in detail.

Model

Figure 6.1 shows the results for the analysis of the SEM model and the hypotheses. Each hypothesis is represented in the model as either a link between two latent variables, or a link that moderates a relationship between two latent variables, with the exception of the control variables to the right hand of job performance. The latent variables of interest are represented by ovals. ML and MN are formative, while job satisfaction, job performance, and organizational commitment are reflective in nature. The latent variables are reduced to individual scores using the factor-based PLS Type CFM1 outer model analysis algorithm, since it "generates estimates of both true composites and factors, in two stages, explicitly accounting for measurement error" (Kock, 2015c, p. 22). Thus, the latent variables are composed of true factors, and not as linear combinations of indicators (Kock, 2015a, 2015b), which is a perceived limitation of Wold's PLS algorithms (Kock, 2015c). The default algorithm for the inner model analysis is set to Warp3. This algorithm allows the software to find the best fitting curve for the relationships being examined (Kock, 2015c). The resampling method is set to Stable 3, since it is recommended as being the more accurate one (Kock, 2015c). The individual settings for the algorithm of the inner model are changed from Warp3 to linear for the link between ML and job satisfaction and the link between ML and organizational commitment. This changes ensure that the moderating effect of MN on these relationship is not captured by as a nonlinear relationship between ML and job satisfaction or ML and organizational commitment (Kock, 2014, 2015c).

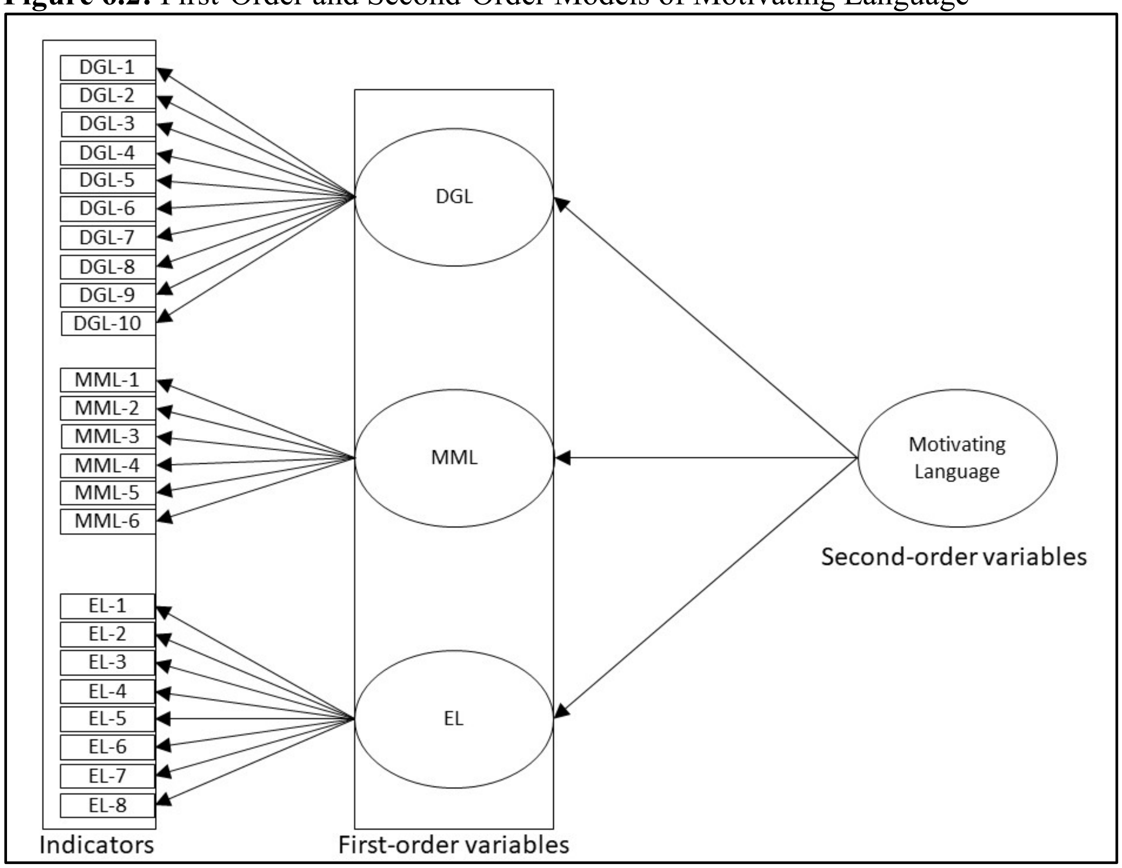
Figure 6.1: Research model with path coefficients and their p-values
(*) P-Value ≤ 0.05; (**) P-Value ≤ 0.01; (***) P-Value < 0.001; Paths with no coefficients are labeled NS



At this point it is important to remember that both ML and MN are constructed as second-order variables. As discussed previously, this is due to the fact that ML has been a second-order construct since the theoretical framework was first proposed by Sullivan (Sullivan, 1988). It is for this reason that when the measurement scale for ML was first developed, it was implemented as a second-order latent variable in a structural equation model (J. Mayfield et al., 1995). Therefore, it logically follows that the measurement of the degree of naturalness that is used in communicating ML should similarly be a second-order latent variable, since MN is measured at the indicator level of ML. As can be seen in the figures 6.2 and 6.3, there are no relationships established between the variables, since the purpose of this step is to produce indicators for the second-order model. The algorithm options for WarpPLS 6.0 that were used in the first-order model are the same as for those specified in the second-order model.

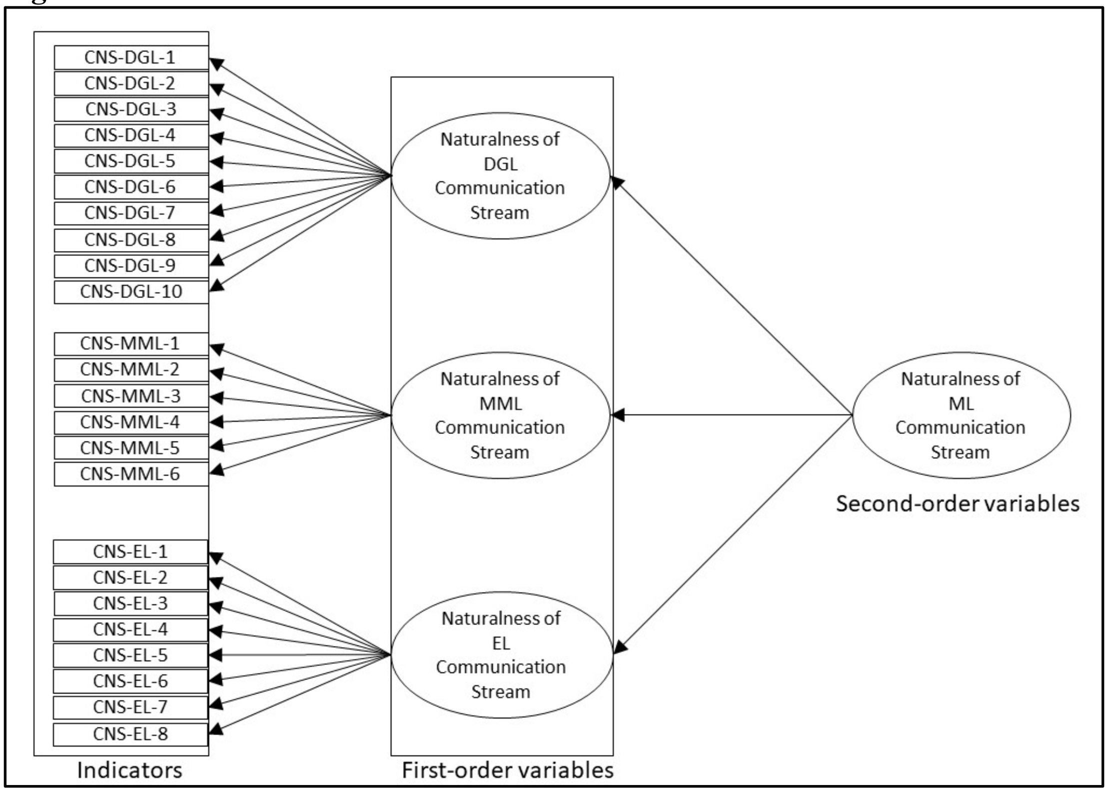
In order to construct ML and MN as second-order latent variables, it was first necessary to construct the three dimensions that compose ML from their respective indicators. As discussed previously in the literature review section, the three dimensions of ML are: DGL, EL, and MML. The measurement scale for ML indicates that DGL is composed of 10 indicators, EL is composed of 6 indicators, and MML is composed of 8 indicators (J. Mayfield et al., 1995). After each of these three dimensions has been constructed into three latent variables for ML and three latent variables for MN. The next step is to perform the SEM analysis and save the latent variables as standardized indicators (Kock, 2015c).

Figure 6.2: First-Order and Second-Order Models of Motivating Language



DGL = Direction Giving Language; MML = Meaning Making Language; EL = Empathetic Language

Figure 6.3: First-Order and Second-Order Models of Media Naturalness



DGL = Direction Giving Language; MML = Meaning Making Language; EL = Empathetic Language
"CNS-" = Communication Naturalness Score for the corresponding Motivating Language indicator

Overview of Results

The effect that ML has is moderated by MN. The results in Figure 6.1 also show that the use of ML is positively correlated with MN, which indicates that some supervisors are at least implicitly aware that in order to improve outcomes, ML is best communicated by more natural media.

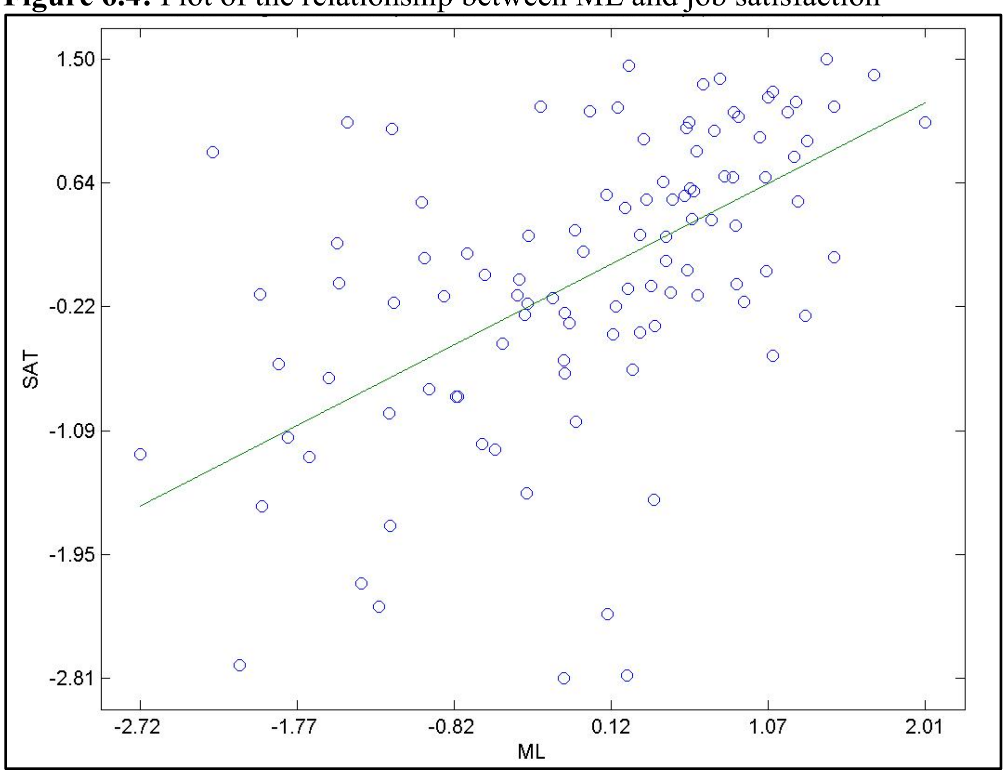
Hypothesis 1 proposes an association between a supervisor's use of ML and job satisfaction. A significant association was found to have a path coefficient of 0.59 and a P<0.001. This indicates that the study finds that the use of ML by a supervisor leads to job satisfaction, which is consistent with previous literature (J. Mayfield & Mayfield, 2007).

Figure 6.4 presents a visual representation of the positive association between ML and job satisfaction. This relationship was manually set to linear in WarpPLS 6.0 as recommended by Kock (Kock, 2015a), since the presence of moderating variables can be captured by a nonlinear relationship.

Table 6.14: Summary of support for hypotheses

	Path Coefficient	P Value	Supported?
H1: ML is positively associated with job satisfaction.	0.59	P<0.001	Yes
H2: ML is positively associated with organizational commitment.	0.61	P<0.001	Yes
H3: Job satisfaction is positively associated with job performance.	0.24	P≤0.01	Yes
H4: Organizational commitment is positively associated with job performance.	0.19	P≤0.05	Yes
H5: The association between ML and job satisfaction is moderated by MN used to communicate said language.	0.20	P≤0.05	Yes
H6: The association between ML and organizational commitment is moderated by the MN used to communicate said language.	0.23	P≤0.01	Yes
H7: The use of ML is positively associated with MN.	0.43	P<0.001	Yes

Figure 6.4: Plot of the relationship between ML and job satisfaction



In a similar manner, Hypothesis 2 proposes an association between a supervisor's use of ML and organizational commitment. A path coefficient of 0.61 and a $P<0.001$ show a significant association. This association indicates that the study finds that the use of ML by a supervisor leads to higher organizational commitment, which is consistent with the literature (J. Mayfield & Mayfield, 2010; J. Mayfield et al., 1998).

Figure 6.5 shows a visual representation of the positive association between ML and organizational commitment. Once again, this relationship was manually set to linear in WarpPLS 6.0 as recommended by Kock (2015c).

Hypothesis 3 proposes that there is a relationship between job satisfaction and job performance. A path coefficient of 0.24 and a $P\leq0.01$ show a significant association. This association indicates that the relationship between the two latent variables is confirmed.

Figure 6.6 shows a plot of the relationship between job satisfaction and job performance. In this case, the relationship was set to Warp 3 in WarpPLS 6.0. This setting means that the relationship is nonlinear with three slopes and two points of inflection. The path coefficient indicates that greater job satisfaction leads to better job performance. Even though the shape of the curve is counterintuitive, there is the possibility that it is being warped by the presence of hard-working employees who are dissatisfied with their jobs.

Hypothesis 4 proposes that there is an association between organizational commitment and job performance. A path coefficient of 0.19 and a $P\leq0.05$ show a significant association. This association indicates that the relationship between the two latent variables is confirmed.

Figure 6.7 shows a plot of the relationship between organizational commitment and job performance. In this case, the relationship was set to Warp 3 in WarpPLS 6.0. This setting means

Figure 6.5: Plot of the relationship between ML and organizational commitment

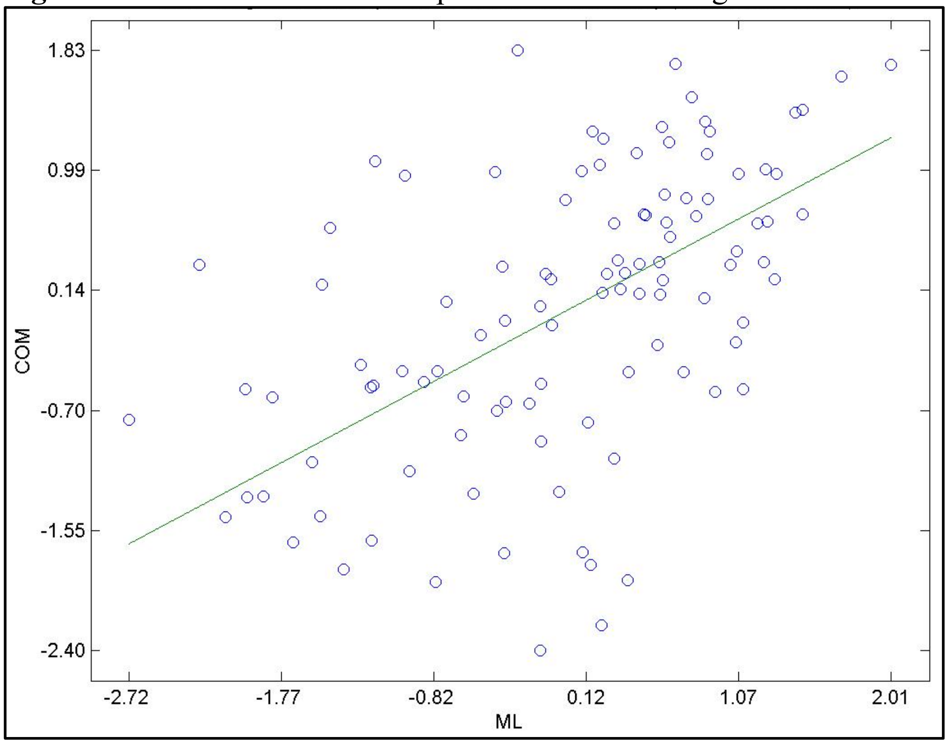
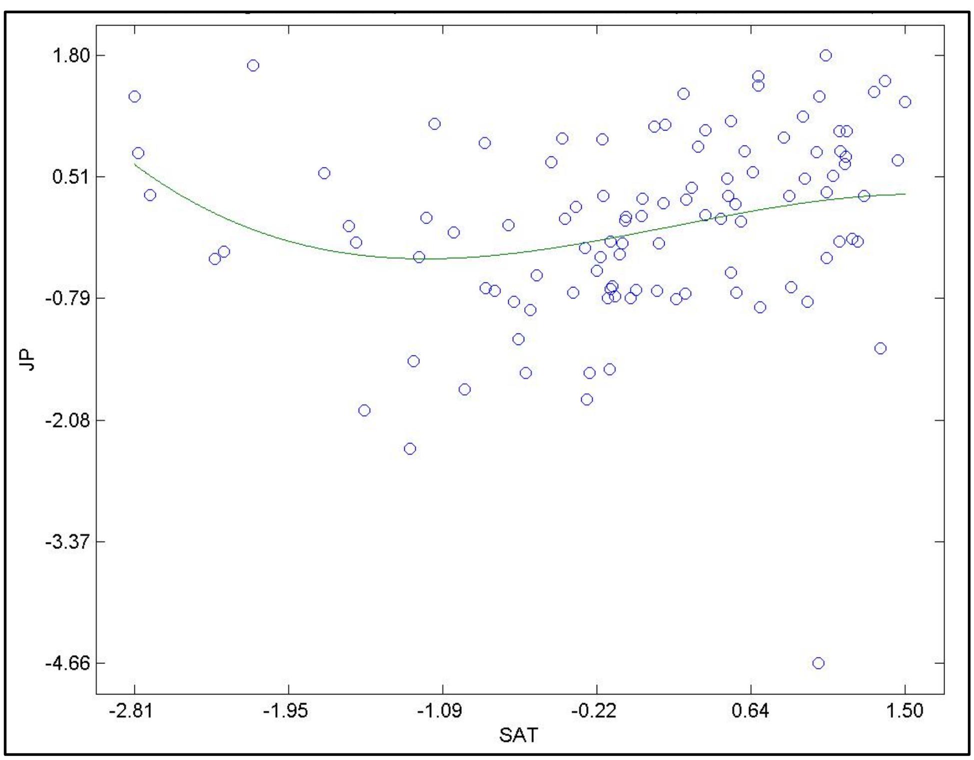
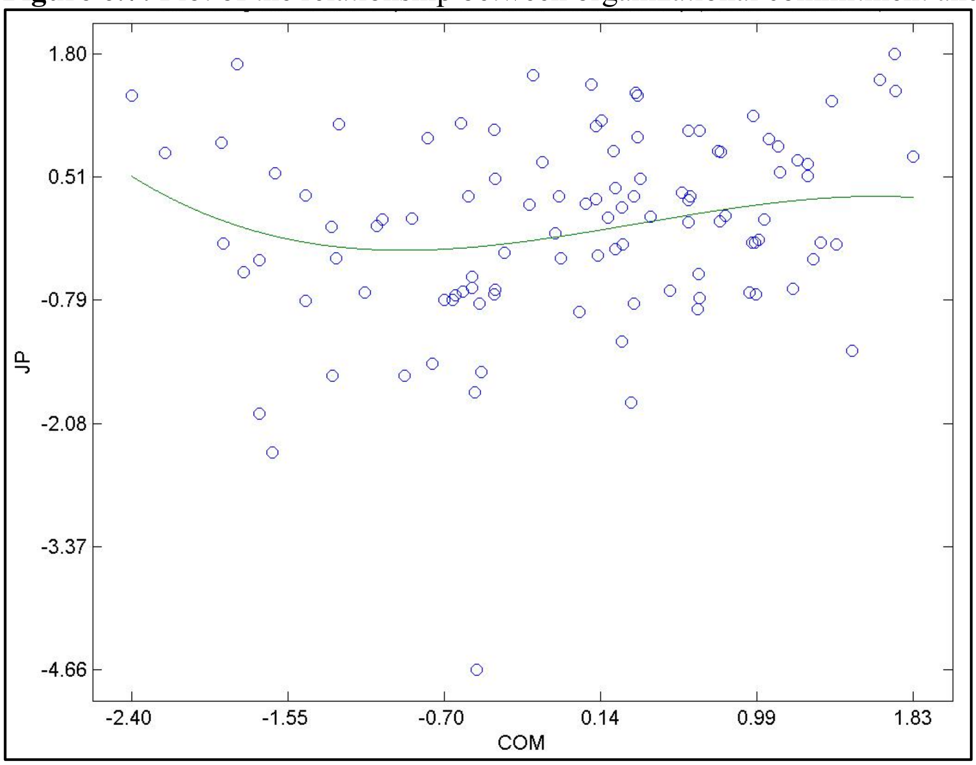


Figure 6.6: Plot of the relationship between job satisfaction and job performance



that the relationship is nonlinear with three slopes and two points of inflection. The path coefficient indicates that greater job satisfaction leads to better job performance.

Figure 6.7: Plot of the relationship between organizational commitment and job performance



Hypothesis 5 proposes that the relationship between ML and job satisfaction is moderated by MN. MN indeed significantly moderates this relationship. This moderating effect has a path coefficient of 0.20 and a P≤0.05. The results indicate that the use of a communication medium with a higher degree of naturalness increases the effect that ML has on job satisfaction.

Figure 6.8 shows a 3D graph with all three variables where the interaction effect can be seen more clearly.

Figure 6.9 shows a plot where MN is split between high and low levels along its median. The figure shows how the effect of ML on job satisfaction is diminished when a lower

Figure 6.8: Rocky 3D graph denoting the moderating effect of MN on the relationship between ML and job satisfaction (standardized scales)

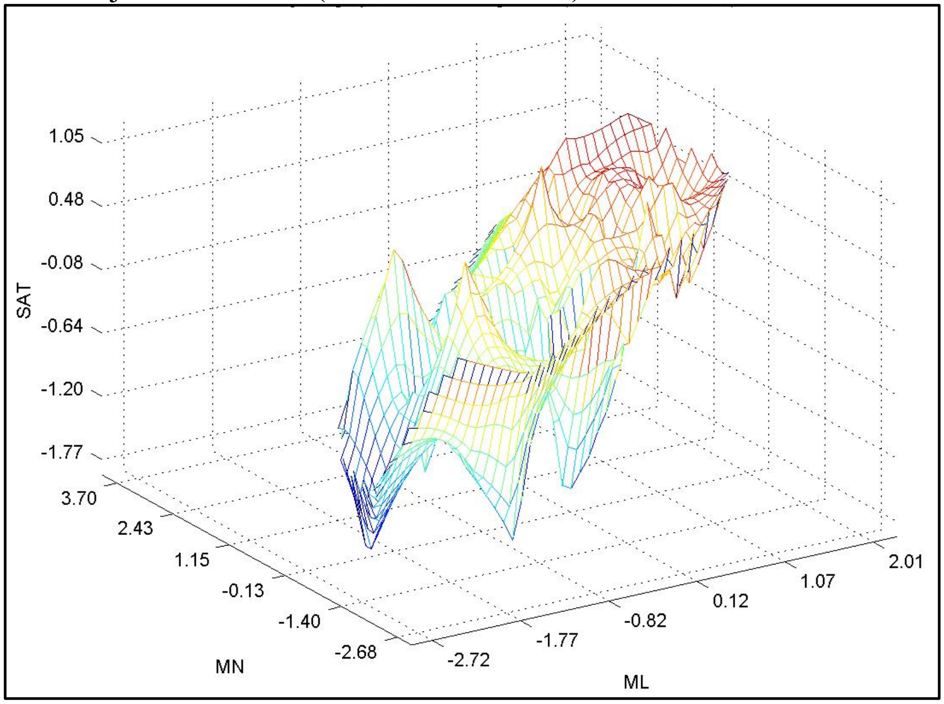
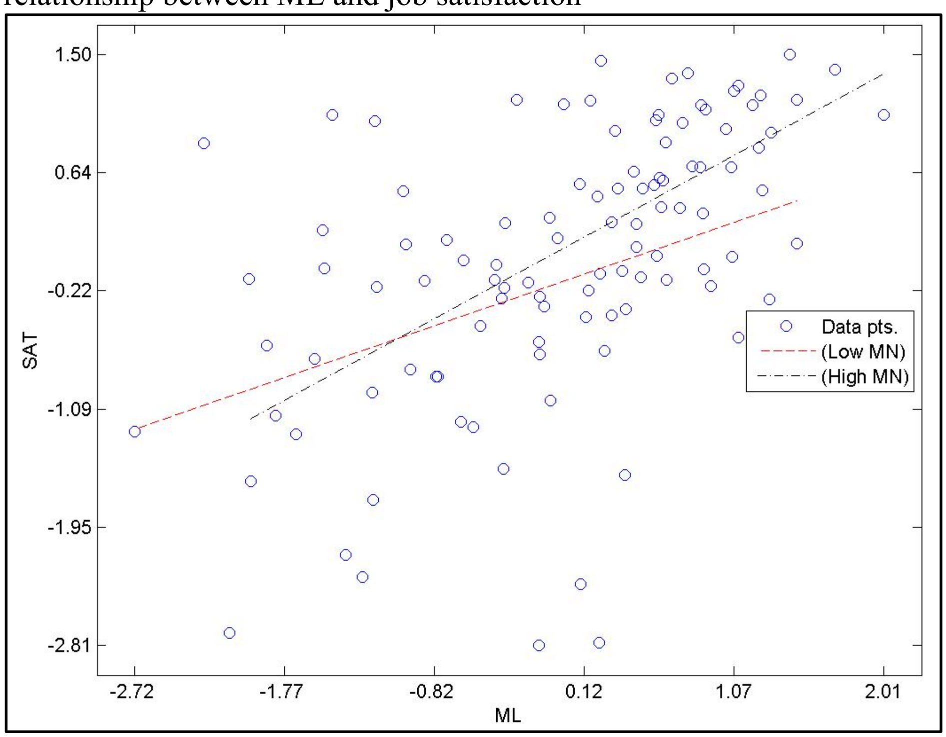


Figure 6.9: Plot graph denoting the moderating effect of high and low levels of MN on the relationship between ML and job satisfaction



naturalness communication media mix is used as compared to when a higher degree of naturalness is used as indicated by their different slopes.

Hypothesis 6 proposes that the relationship between ML and organizational commitment is moderated by MN. MN indeed significantly moderates this relation. This moderating effect has a path coefficient of 0.23 and a $P \leq 0.01$. The results indicate that the use of a communication medium with a higher degree of naturalness increases the effect that ML has on organizational commitment.

Figure 6.10 shows a 3D graph with all three variables where the interaction effect can be seen more clearly.

Figure 6.11 shows a plot where MN is split between high and low levels along its median. The figure shows how the effect of ML on organizational commitment is diminished when a lower naturalness communication media mix is used as compared to when a higher degree of naturalness is used as indicated by their different slopes.

Hypothesis 7 proposes that the use of ML is associated with MN. As mentioned previously, managers will display a tendency to mix together communication media with a higher degree of naturalness as their use of ML increases. This relationship is positive and significant, which supports the hypothesis. The path coefficient of this relation is 0.43 with a $P < 0.001$.

Figure 6.12 shows a plot of this relationship. In this case, the relationship was set to Warp 3 in WarpPLS 6.0. This setting means that the relationship is nonlinear with three slopes and two points of inflection.

Figure 6.10: Rocky 3D graph denoting the moderating effect of MN on the relationship between ML and organizational commitment (standardized scales)

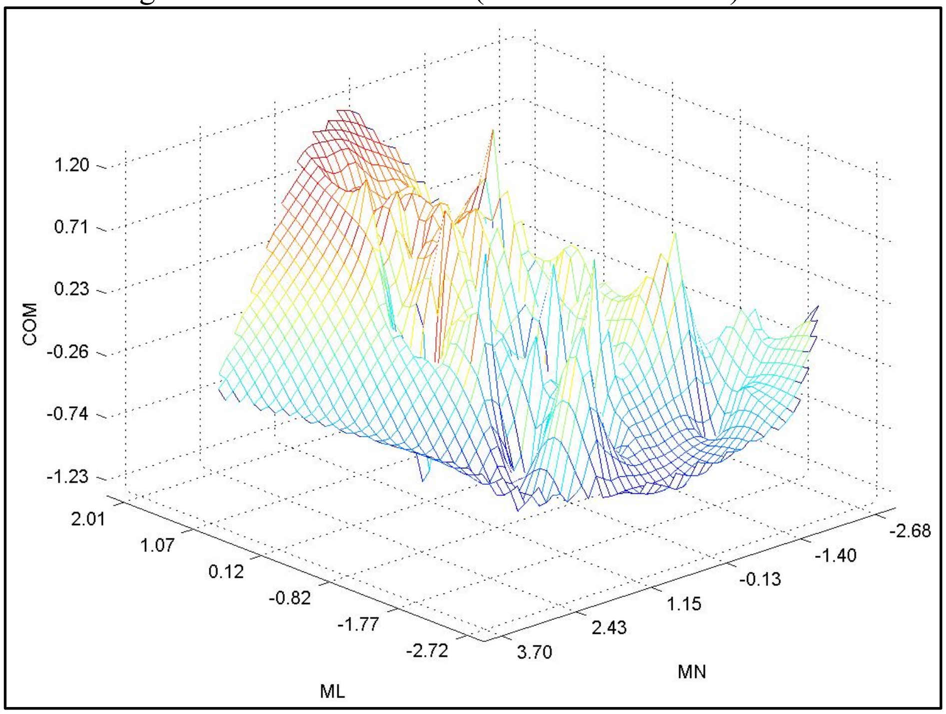


Figure 6.11: Plot graph denoting the moderating effect of high and low levels of MN on the relationship between ML and organizational commitment

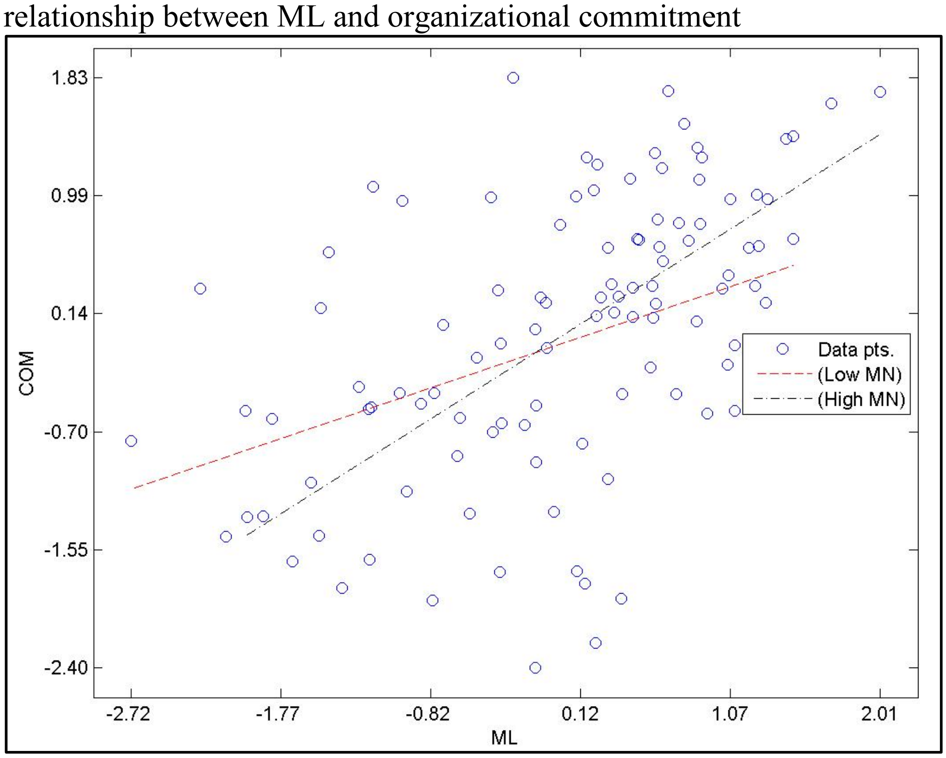
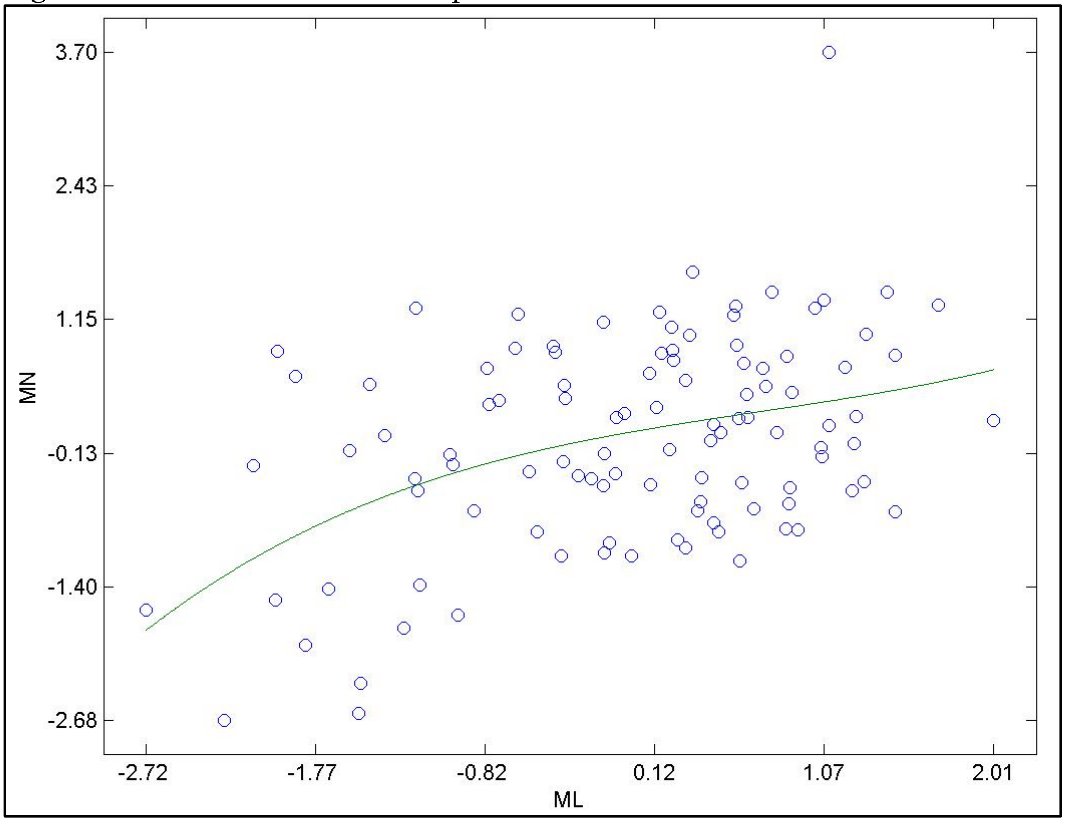


Figure 6.12: Plot of the relationship between ML and MN



Total, Direct, and Indirect Effects

WarpPLS version 5 calculates the indirect as well as the total effects for all the latent variables that are linked by a path with one or more segments. The software provides "The path coefficients associated with the effects, the number of paths that make up the effects, the P values associated with effects (calculated via resampling, using the selected resampling method), the standard errors associated with the effects, and effect sizes associated with the effects. Indirect effects are aggregated for paths with a certain number of segments" (Kock, 2015c, p. 80). The effect sizes are calculated as Cohen's (Cohen, 2009) f-size threshold.

Table 6.15 shows the total effect for ML along with the number of paths that are used in their calculation as well as the effect size and P value. These total effects are calculated automatically taking into account all of the paths that connect the two variables in question (Kock, 2015c).

The effect sizes for job satisfaction, organizational commitment, and MN are considered to be of medium magnitude, while the effect on job performance is considered to be small. According to Cohen's guidelines, a small effect ranges from 0.02 to less than 0.15; a medium effect ranges from 0.15 to less than 0.35, while a large effect is greater than 0.35 (Cohen, 2009).

Table 6.15: Total effects of ML

	Paths	**Total Effect**	**Effect Size**	**P Value**
SAT	1	0.592	0.311	<0.001
COM	1	0.605	0.319	<0.001
JP	2	0.26	0.091	≤0.01
MN	1	0.431	0.186	<0.001

Table 6.16 shows the effect that MN has on job satisfaction, organizational commitment, and job performance through its mediating effect on ML. The effect that it has on job satisfaction is significant at the P<0.05 level, while the effect that it has on organizational commitment is significant at the P<0.01 level, and the effect that it has on job performance is not statistically significant, since it is at the P=0.164 level. This last p-value means that the probability that the effect is true and not a result of chance is 83.6% (1-0.164). The sizes of the effects on organizational commitment and job performance are considered small according to the guidelines previously mentioned.

Table 6.16: Total effects of MN

	Paths	**Total Effect**	**Effect Size**	**P Value**
SAT	1	0.201	0.0	≤0.05
COM	1	0.232	0.007	≤0.01
JP	2	0.094	0.013	Non Significant

Table 6.17 presents the direct effect that ML has on the following endogenous latent

variables: job satisfaction, organizational commitment, and MN. All the sizes of the effects in the table are of medium magnitude according to the aforementioned criteria, as well as being significant at the P<0.01 level. These results show that ML use has a significant and direct effect on job satisfaction, organizational commitment, and the use of a mix of communication media with a higher degree of naturalness.

Table 6.17: Direct effect of ML

	Total Effect	**Effect Size**	**P Value**
ML→SAT	0.592	0.311	<0.001
ML→COM	0.605	0.319	<0.001
ML→MN	0.431	0.186	<0.001

Table 6.18 shows the sum of the indirect effects that ML has on job performance. Since a direct link between ML or MN in not hypothesized, the only effect that this endogenous latent variable has on the former latent variables is an indirect one. This effect is small according to the previously discussed criteria, and its P value is significant at the P<0.01 level. These results show that ML by a supervisor has a small indirect effect on the job performance of an employee.

Table 6.18: Sum of indirect effect of ML

	Paths	**Indirect Effect**	**Effect Size**	**P Value**
JP	2	0.26	0.091	≤0.01

Table 6.19 shows the total of the indirect effects that MN has on job performance. According to the previously mentioned criteria, the effect is so small as to be inconsequential. It is important to note that this effect is not statistically significant, with a P=0.164. As mentioned previously, this P value means that this effect has a 83.6% probability of having occurred by chance (1-0.164).

Table 6.19: Sum of indirect effect of MN

	Paths	Indirect Effect	Effect Size	P Value
JP	2	0.094	0.013	Non-Significant

Table 6.20 shows the total effects that all the latent variables in the model have on the endogenous latent variable job performance. The table shows that job satisfaction has one path pointing to job performance, which has a small effect on the former that is significant at the $P<0.01$ level. This P value means that job satisfaction has a small, but statistically significant effect, on job performance. It also shows that organizational commitment has a small but statistically significant effect on job performance at the $P<0.05$ level.

Table 6.20 also shows that ML has two paths pointing to job performance. The model shows that one of these paths is mediated by job satisfaction, and the other one by organizational commitment. Thus, the effect that ML has on job performance is indirect in nature. As Table 6.20 shows, the size if the effect is small, but once again it is statistically significant. This significance means that the frequency of ML use by a supervisor affects an employee's job performance in a small but measurable manner. The table also shows the indirect effect that MN has on job performance. The size of this effect is below the threshold value to be considered small and is statistically non-significant.

Table 6.20: Total effects of all latent variables on job performance

	Paths	Total Effects	Effect Size	P Values
SAT	1	0.242	0.092	≤ 0.01
COM	1	0.194	0.066	≤ 0.05
ML	2	0.260	0.091	≤ 0.01
MN	2	0.094	0.013	Non-Significant

CHAPTER VII

PRINCIPAL STUDY

Data Collection

The study consists of 500 surveys completed by respondents of various backgrounds and age groups from the US and India. All the surveys were done online and collected by using Google forms. The participants were obtained through Amazon Mechanical Turk. A total of 250 requests were made for participants in the US and in India. From the 250 surveys completed by US respondents, 196 were usable (78.4% acceptance). From the 250 surveys completed by Indian respondents, 165 were usable (66% acceptance). The final sample was 351 surveys.

Amazon Mechanical Turk

The name "Mechanical Turk" was borrowed by Amazon from the eighteenth-century invention of Hungarian nobleman Wolfgang von Kempelen: An automaton capable of beating humans at chess. This turbaned mannequin was attached to a wooden cabinet and was fashioned to resemble a Turk smoking a pipe and toured Europe with great success (Howe, 2006). But the whole arrangement was a hoax: The cabinet in reality hid a flesh-and-blood chess master who, through a complex mechanism of magnetic chess pieces and pantograph style levers, was able to move the left arm of the automaton and direct its movements on the chess board above (Standage, 2002). Thus, it gave the illusion that a machine was doing a task that in reality was being done with human intelligence. This reference is fitting since according to its website, "Amazon Mechanical Turk (MTurk) operates a marketplace for work that requires human intelligence" (Amazon, 2018). In a sense, it provides "artificial artificial intelligence" (Chandler & Shapiro, 2016, p. 55). Among the common uses that are listed are image and video processing, data verification and cleanup, data processing, and data gathering. Much like the original

Mechanical Turk, most of these tasks are done as background processes in business service or web applications, so that it appears that they are actually done by computers. But some of the other applications listed in the information gathering section of the Amazon Mechanical Turk website are more transparent, such as obtaining market research information and survey data (Amazon, 2018), and it is widely used as a source of respondents in academic research (Buhrmester, Kwang, & Gosling, 2011).

Crowdsourcing has diversified into multiple and sometimes unexpected areas since its earlier days of open source software development. It is now used in areas such as photography, research and development, and content generation (Howe, 2006). It is thus only natural that the crowdsourcing phenomenon would eventually find its way into academic research. After all, with the increased availability of large pools of participants for such a wide range of tasks and the increased notoriety of various crowdsourcing platforms, this occurrence was just a matter of time. In fact, as early as 2008 academics were quick to seize this opportunity after Kittur, Chi, and Suh (2008) published their guide on how to use MTurk as a subject pool. It should thus be no surprise that it is not uncommon to find empirical research that uses data collected entirely from MTurk (Paolacci & Chandler, 2014).

Advantages of Mechanical Turk

The advantages of using MTurk are quite numerous. First, MTurk has a large pool of possible participants (Shapiro, Chandler, & Mueller, 2013); a pool that is much more varied than the traditional convenience samples and slightly more varied than ordinary internet samples (Berinsky, Margolis, & Sances, 2014). This large pool is part of what makes gathering data from Amazon's MTurk quick and relatively inexpensive without these necessarily coming at the expense of quality (Buhrmester et al., 2011). The fact that this pool is more varied can make it easier to reach participants in various other countries or underrepresented and traditionally hard to reach groups (Shapiro et al., 2013). These characteristics can in turn lead to other advantages, such as faster design iterations of surveys and experimental studies.

Concerns with using MTurk

The issue of whether a sample is representative of a population or not is a recurring one, and especially so when convenience samples are used. This is true whether these samples are obtained by conducting surveys in person in or around a university campus, distributed online, or by using some form of crowdsourcing, like MTurk. While Turkers are more diverse than most convenience samples (Berinsky, Huber, & Lenz, 2011; Kittur et al., 2008), they are not necessarily representative of their respective populations in ways that are similar to the differences between internet users and non-internet users (Paolacci & Chandler, 2014), which can raise issues about the study's generalizability (Mason & Suri, 2012).

A concern that has become apparent in some academic research circles with the rise in popularity of MTurk is that of the possible Nonnaïveté in the population. This concern may not be as well known, but it is no less important. Since Turkers are likely to remain on the platform longer than students remain in a university, it can be more likely that a Turker is familiar with surveys in topics that are related to the one the researcher is using. Then there is also the fact that there are forums that are specific to Turkers where studies, requesters, and Human Intelligence Tasks (HITs) are discussed. Thus, the respondent may be familiar with how to answer the survey, which may negatively affect the validity of the data (Chandler, Mueller, & Paolacci, 2014). The author does not consider Nonnaïveté of the participants to be an issue to the current study, since no empirical research exists to date on the topic of MNT. Further, the current study has only been done once in MTurk over a short period of time that does not give Turkers the opportunity to comment on the HIT in the relevant online forums.

Another source of concern is inattentiveness, Gaming, use of bots, and low quality data. These concerns stem mainly from the fact that MTurk is a fast and cheap source of data: If it is fast and cheap, what is the downside? How are people gaming the system? The easiest form of gaming the system is by simply being inattentive while answering a survey in order to collect the reward. However, experiments have shown that there is little or no effect from the wage on the quality of MTurk results (Mason & Suri, 2012). Although some have reported indications that auto completing bots may be submitting responses (McCreadie, Macdonald, & Ounis, 2010), it is not common (Mason & Suri, 2012). In the same vein, the research has shown that a Turker's approval rating is a good indicator of the quality of his or her responses (Peer, Vosgerau, & Acquisti, 2014). These issues were addressed by the author by requiring Turkers to have an approval rating of 90% or more and with more than 100 HITs completed and the use of an attention screening question.

Mechanical Turk in Current Academic Research

Examples of MTurk being used to gather data for academic research can be found in a plethora of fields. In Psychology, Buhrmester et al. find that Turkers are more diverse than traditional internet samples and significantly more diverse than American college samples. They also find that while task length and compensation rate affect participation in a study, participants can still be recruited rapidly and inexpensively and that the data obtained are at least as reliable as traditional methods (Buhrmester et al., 2011). In the field of Organizational Psychology, Landers and Behrend (2015) argue that most sampling by definition is some variation of a convenience sample and thus advocate for the wider acceptance of other forms of convenience sampling: online panels and crowdsourcing in general, and MTurk in particualr. Although the previous article suggests that there is a tendency in this field to not accept studies that use MTurk as a resource for scholarly research, the survey of the top 20 journals in the field by Cheung, Burns, Sinclair, and Sliter (2017) finds 99 empirical papers with at least one MTurk sample. In the field of Clinical Psychology, Shapiro et al. argue that MTurk is a convenient way of locating and recruiting participants for research that requires subjects with specific risk factors or rare demographic characteristics and provides the participant and researcher the additional benefit of guaranteed anonymity. The authors then proceed to conduct mental health surveys and report that the quality of the data obtained by these means is high (Shapiro et al., 2013).

In the field of Behavioral Research, Mason and Suri (2012) share their experience in conducting surveys and experiments using MTurk as a participant pool. Notably, they provide several guides on how to do synchronous experiments in MTurk as well as a guide for using MTurk to help in debugging the design of the experiment. In the field of Political Research, Clifford et al. examine "whether liberals and conservatives recruited from MTurk share the same psychological dispositions as their counterparts in the mass public" (Clifford, Jewell, & Waggoner, 2015, p. 1). They do this by comparing a large MTurk sample to two other national benchmark samples. One of these was obtained face-to-face and the other online. They find that the three samples produce "substantively identical results with only minor variations in effect sizes" (Clifford et al., 2015, p. 1) and that MTurk is a valid tool for recruiting participants in psychological research in the field of Political Ideology. In the field of Political Science, Yale University's Huber and Paris (2013) conduct a study by analyzing a short survey filled through MTurk that challenges the long taken-for-granted programmatic equivalence of welfare and assistance to the Poor. They then proceed to posit that Americans actually differ in which programs are actually associated with each of these labels. In the field of Political Science and

International Relations, Tomz and Weeks (2013) study the phenomenon known as “Democratic Peace” in which a democracy is less likely to attack another democracy than another type of regime. They conduct the study in the United Kingdom by using the internet polling agency YouGov, and in the United States by using MTurk. They find support for the Democratic Peace phenomenon without the shortcomings of the previous survey studies that relied mostly on smaller sample sizes or college student convenience samples.

The use of MTurk in this Study

An MTurk requester account was created, and a form of payment was entered as required by MTurk. After reading various online recommendations on how to create HITs on MTurk and asking for recommendations, the author decided that the best approach was to create a HIT in MTurk that would link to a survey that had already been created in Google forms. The author proceeded to create a test HIT to ensure that any potential bugs were removed before conducting the study. After this, the author examined the options for restricting the participant pool. The options that were used were geo location, age, full time employment status, HIT approval, and number of HITs approved.

Geo location restricts the participants to residents of the target countries of India and the United States. Age ensures that all participants were 18 years old or older, which conforms to the Internal Review Board’s requirements. Full tine employment status was requested in order to avoid the presence of confounding variables, since studies have shown that employment status is a moderator of the effect that ML has on organizational outcomes (J. Mayfield & Mayfield, 2006). The minimum HIT approval rating for Turkers was set at 90%, and the minimum number of HITs completed was set at 100, following published recommendations (Peer et al., 2014).

The next step was to request HITs with the purpose of debugging the process. The author initially submitted a HIT with one assignment (response to the survey) to which the author responded using someone else's account. This was done in order to become familiar with what the Turkers would see when responding to the HIT. After this, a test batch of 93 HITs was submitted but was stopped after 23 HITs were completed when the author realized that he had failed to provide Turkers with a unique identifier. This was corrected in the subsequent batches by asking the respondents to enter the MTurk ID at the end of the survey. The potential participants were told before accepting the HIT that the ID was required to complete the survey and thus get the reward of $0.75.

Upon working out these bugs, the author proceeded to create two separate batches of 250 HITs with the additional restriction that each Turker could only participate once in each batch to ensure no multiple responses. One of the batches had the geographical restriction of Turkers with IP addresses in the United States, and the other one was restricted to IP addresses in India. This way the author aimed to receive 250 responses from each of the two target countries. As was mentioned earlier in the study, both surveys were identical and in English, since use of the English language is widespread in India. However, each of these batches contained the link to a separate Google form, so that the answers would be saved in different Google Sheets, thus keeping the two samples separate.

The gathering of the data was extremely fast, but more so for the US sample. According to the timestamps on Google Sheets, the first survey form the US sample was submitted on 2/03/2018 at 5:26 PM, while the last one was submitted on 2/04/2018 at 12:15 AM, while MTurk reported the average time spent on each HIT as 23 minutes. The process of collecting all 250 responses for the US sample took 6 hours and 49 minutes. The sample from India was not quite as fast. The timestamps on Google Sheets indicate that the first survey was collected on

2/03/2018 at 5:30 PM, and the last one was submitted on 2/5/2018 at 11:07 AM. The process of collecting the responses for the India sample took a total of 1 day, 17 hours, and 7 minutes while MTurk reported the average time spent on each HIT as 25 minutes.

The total cost for the data collection was as follows: Each Turker was offered a reward of USD $0.75. The Mechanical Turk fee from Amazon was $0.30 per HIT, plus a $0.35 per HIT for filtering the respondent pool according to employment status. These costs equaled $1.40 per survey for a total cost of USD $350.00 for collection of the US sample plus another USD $350.00 for the collection of the India sample, which brought the total cost of collecting the surveys for this study to $700.00.

Data Preparation

For the initial stage of data preparation, the date was visually examined on both samples. When examining the US sample, the author found that one respondent reported being unemployed. The respondent was dropped from the sample, since in this case it is impossible to identify whether the respondent was answering the survey keeping the last job in mind, or a combination of previous jobs. Eight respondents reported being employed part-time. They were also dropped from the sample to avoid confounding variables, since part-time employment has been shown to have an effect on ML (J. Mayfield & Mayfield, 2006), as noted previously. Another 21 respondents reported being born outside of the United States. They were also dropped from the sample to avoid introducing noise to the US sample, since the purpose of the study is to measure the moderating effect of MN on ML, and there is no practical way to determine "how Americanized" these respondents are, or to measure how their responses would vary from those respondents born in the United States. Finally, another 30 respondents failed to indicate that they disagreed to having a heart attack while answering the survey. These respondents were dropped, since this answer indicates inattentiveness (Berinsky et al., 2014). This reduced the number of usable responses from 250 to 196 for the US sample.

Upon examining the India sample, the author found that one respondent reported being unemployed. The respondent was dropped from the sample, since in this case it is impossible to identify whether the respondent was answering the survey keeping the last job in mind, or a combination of previous jobs. Five respondents reported being employed part-time. They were also dropped from the sample to avoid confounding variables, since part-time employment has been shown to have an effect on ML (J. Mayfield & Mayfield, 2006). Although some respondents reported being born in the United States or England, they were not dropped from the study. The reason for not excluding them is that it is not uncommon for parents living abroad to bring their children back with them to their country of origin, in this case India. Finally, another 77 respondents did not disagree to having a heart attack while answering the survey. These respondents were dropped, since this can be seen as an indicator of inattentiveness (Berinsky et al., 2014). These exclusions reduced the number of usable responses from 250 to 165 for the India sample

Finally, the communication naturalness score was calculated for every respondent of the two samples. This was done at the ML indicator level for each of the 21 indicators in the MLT measurement scale (J. Mayfield et al., 1995). Since ML is specified as a second-order latent variable (J. Mayfield et al., 1995). This was done with a in order to adhere to the methodology detailed in the MN section of Chapter IV.

Cultural Manipulation Checks

In order to substantiate that the US and India samples were indeed collected from culturally distinct populations, cultural manipulation checks were conducted. As in Moqbel

(Moqbel, 2012), this study includes 15 questions that were adopted by the cultural dimensions study conducted by Hofstede (Hofstede, 1980, 1984, 1993, 2001). This analysis shows that both samples were “treated” by exposure to different cultures, thus confirming that the samples were indeed obtained from the countries stated. Although many studies have criticized Hofstede’s study of cultural dimension and at times quite harshly as evidenced by the title of the articles *Hofstede’s model of national cultural differences and their consequences: A triumph of faith - a failure of analysis* (McSweeney, 2002b), or *The essentials of scholarship: A reply to Geert Hofstede* (McSweeney, 2002a). However, Hofstede’s work remains relevant and well cited decades after its initial and subsequent publications. According to Google Scholar, Hofstede has a total of 156,756 citations with 26,232 of those being of his 2001 re-written version of the *Culture’s Consequences* book, while 54,332 are of his first version of the same book (Google, 2018). Geert Hofstede himself mentions that in the first version of his *Culture’s Consequences* book there are 90 “significant and independent correlations” to his cultural dimensions, while for his 2001 revised edition he cites 1,500 sources of 400 correlations to the same (Hofstede, 2002).

Each of the five cultural dimensions in the above study has three indicators in the instrument used in this study, as in Moqbel (2012) (see appendix B). The cultural dimension scores for both the United States and India are listed in the Hofstede (2001) study and were part of his original IBM study. In the power distance dimension, India receives an index of 77 and a rank of 11, while the United States receives an index of 40 and a ranking of 38. The index differential for this dimension is 37, and a ranking differential of 27. In the uncertainty avoidance dimension, India receives an index of 40 and a rank of 45, while the United States receives an index of 46 and a ranking of 43. The index differential for this dimension is 6, and a ranking differential of 2. In the individualism-collectivism dimension, India receives an index of 48 and a rank of 21, while the United States receives an index score of 91 and a rank of 1. The index differential is 43, and the rank differential is 20. In the long term-short term orientation dimension, India receives an index of 67 and a rank of 7, while the United States receives an Index of 29 and a rank of 27. The index differential for this dimension is 32, and the rank differential is 20. Table 7.1 shows the index scores and rankings for India and the United States for comparative purposes.

Table 7.1: Cultural Manipulation Checks: Country indices and rankings

	Power Distance		Uncertainty Avoidance		Individualism/ Collectivism		Masculinity/ Femininity		Long Term/ Short Term Orientation	
	Index	Rank	Index	Rank	Index	Rank	Index	Rank	Index	Rank
US	40	38	46	43	91	1	62	15	29	27
India	77	11	40	45	48	21	56	20	61	7

While it would be tempting to predict that the differences that we expect to find correspond directly to the differences in Hofestede's study, this expectation would entail a de-facto replication of the latter. In the section of the study titled *Replications and their Pitfalls*, the author warns about several complications, including the following: "Therefore, cross-national research should be done only on *matched samples* – that is, samples similar in all respects except nationality." (emphasis in italics by Hofstede) (Hofstede, 2001, p. 463). In this manner, Hofstede himself warns that this study cannot attempt to uncover similar findings without carefully matched samples. The author of the current study takes these remarks seriously and therefore does not attempt to replicate the study as evidenced by the fact that each dimension is replicated in the measurement instrument by just three indicators and not the original instrument. Therefore, it is expected that this study will not necessarily find results that are consistent with his studies. Because of this, rather than replicating the direction and magnitude of the cultural dimensions, the purpose of the cultural manipulation checks is *only* to show that as evidenced by their different responses on the cultural dimension items, both the US and India samples are indeed drawn from culturally distinct populations.

WarpPLS 6.0 was used to conduct the cultural manipulation check. This was done by using a country variable dummy and pointing it at each of the five cultural dimensions. These were operationalized as latent variables composed of three indicators as mentioned previously. If the path coefficients are statistically significant, they indicate the presence of a significant variability between the India and the US samples for that particular cultural dimension. Table 7.2 shows the results of the cultural manipulation checks. These show that both samples are statistically different in three of the five cultural dimensions that confirms the participants from India and the United States were from culturally distinct populations.

Table 7.2: Cultural Manipulation Checks: Path coefficients and P values

	Power Distance	Uncertainty Avoidance	Individualism/ Collectivism	Masculinity/ Femininity	Long Term/ Short Term Orientation
Absolute Path Coefficient	0.03	0.008	0.10*	0.16***	0.12**

(*) P-Value = 0.05; (**) P-Value = 0.01; (***) P-Value = 0.001. A significant path coefficient indicates that a statistical difference between the US and India samples in the related cultural dimension. Data and scores are from Hofstede's 2001 book that uses the original IBM study (Hofstede, 2001)

The use of the US and India subsamples as one joint sample

A multigroup analysis was conducted on the US and India subsamples. The results indicate that although the samples are from two different countries, there is no statistical difference between the US and India subsamples regarding the factor loadings on the latent variables, or in their measurement models. The data from each subsample can be used jointly with the purpose of achieving higher statistical power in the study.

The next section will discuss the principal statistical algorithms and methodologies that will be employed throughout the study.

Partial Least Squares

The data are analyzed using structural equation modeling, which is a second-generation statistical analysis technique that is used to estimate the parameters in a structural model. The main goal of SEM is to test models that specify relationships between variables (Schumacker & Lomax, 2004). One of the reasons for its rise in popularity among researchers is that it takes measurement error into account when analyzing the data (Kock, 2017). SEM tools can be covariance-based (such as LISREL) or variance-based like those that partial least squares (PLS), such as WarpPLS.

Some of the implicit assumptions that must be fulfilled for the covariance-based SEM can be problematic, require larger sample sizes, and require multivariate normality in the data (Hair et al., 2011). These requirements can be especially so in the field of social sciences, since survey data is in many cases not normally distributed (Kock, 2017). Additionally, the covariance-based SEM has certain restrictions that make it inappropriate for certain kinds of studies. One such restriction is a basis in sound theory, since it "develops a theoretical covariance matrix" (Hair et al., 2011, p. 139) and tries to minimize the variance between this matrix and the estimated covariance matrix. This restriction is adequate for confirmatory research, but inadequate for research that is exploratory in nature or "an extension of an existing structural theory" (Hair et al., 2011, p. 144). While the purpose of the present study is not that of extending an existing structural theory, its testing of the central hypothesis of the study can be seen as an extension of the structural theory of ML from a strictly technical perspective, since new latent variables and relationships between them are introduced to the model.

PLS SEM on the other hand is a second-generation multivariate variance-based technique that estimates the parameters of the structural model. Additionally, it does not require an established theory and can thus be used for exploratory research. It also overcomes various other limitations imposed on covariance-based SEM: it is able to use smaller sample sizes, is able to analyze more complex models, can implement formative or reflective latent variables, and does not require the indicators or latent variables to conform to multivariate normality (Chin, 1998; Hair et al., 2011).

The implementation of PLS is not exclusive to SEM: it can also be applied in regression or path modeling. This study uses WarpPLS 6.0 for the analysis that is a nonlinear variance-based SEM that uses PLS regression in its implementation of the SEM. Unlike other SEM and PLS regression tools, WarpPLS can identify many different kinds of nonlinear relationships that may occur within the model (Kock, 2017). This can be particularly useful, since many relationships including behavioral variables are likely to be nonlinear in nature (Kock & Gaskins, 2016). The software provides various options of resampling algorithms such as jackknifing, bootstrapping, blindfolding, and stable methods. The default resampling method for WarpPLS 6.0 is Stable3, which not only yields more precise estimations of the standard errors than jackknifing or Stable1, for example, but is also more computationally efficient (Kock, 2017).

Model Assessment

In the following sub-sections various forms of assessing the adequacy of the structural equation model.

Descriptive Statistics

Table 7.3 presents the maximum and minimum values as well as the median and mode for the latent variables in the model. Skewness and kurtosis coefficients are also reported and the Jarque-Bera test of normality. The means are not presented, since WarpPLS normalizes the data of all the indicators before calculating the values of the latent variables. However, only one of the five variables (MN) is normally distributed in the multivariate space as indicated by its skewness and kurtosis coefficients and the Jarque-Bera test of normality. Table 7.4 presents the indicator correlation matrix for the second-order model.

Table 7.3: Latent Variable Summary Statistics

	Job Satisfaction	Organizational Commitment	Job Performance	Motivating Language	Media Naturalness
Minimum Value	-2.879	-2.708	-5.229	-3.233	-3.121
Maximum Value	1.508	1.754	1.868	2.065	2.883
Median	0.207	0.166	0.044	0.116	-0.131
Mode	-2.879	-2.708	-5.229	-3.233	-3.121
Skewness Coefficient	-0.895	-0.497	-0.855	-0.587	0.08
Kurtosis Coefficient	0.454	-0.565	2.089	0.09	0.397
Jarque-Bera test of Normality	No	No	No	No	Yes

Validity

The proposed model is evaluated by using variance-based SEM), which is a powerful multivariate analysis technique that is frequently used for complex causal models (Chin, 1998) such as this one. The advantage of PLS-SEM versus covariance-based SEM is that it uses non-parametric techniques such as resampling, so it implicitly makes no assumptions about the distribution of any of the variables involved or any of their indicators. These techniques make it suitable for situations in which one or more of the criterion variables are not normally distributed (Hair et al., 2011; Siegel, 1956) as well as providing better accuracy and statistical power when smaller samples are used (Kock, 2015a; Kock & Hadaya, 2018).

The SEM comprises a measurement (outer) model structural model and a structural (inner) model (Kock, 2015a). The measurement model tests whether the latent variables in the

Table 7.4: Indicator Correlation Matrix

	LD	LE	LM	MD	ME	MM	SAT1	SAT2	SAT3	SAT4	SAT5	COM1	COM2	COM3	COM4	COM5	JP1	JP2
LD	1																	
LE	0.853	1																
LM	0.722	0.699	1															
MD	0.169	0.222	0.027	1														
ME	0.216	0.284	0.051	0.853	1													
MM	0.331	0.351	0.317	0.588	0.646	1												
SAT1	0.612	0.601	0.471	0.118	0.164	0.18	1											
SAT2	0.616	0.611	0.473	0.078	0.154	0.183	0.826	1										
SAT3	0.608	0.591	0.468	0.077	0.132	0.141	0.778	0.827	1									
SAT4	0.595	0.57	0.437	0.149	0.195	0.212	0.834	0.809	0.812	1								
SAT5	0.608	0.577	0.44	0.103	0.151	0.193	0.734	0.709	0.69	0.73	1							
COM1	0.598	0.55	0.451	0.098	0.151	0.139	0.748	0.723	0.688	0.739	0.686	1						
COM2	0.626	0.591	0.471	0.093	0.143	0.18	0.734	0.75	0.758	0.777	0.649	0.758	1					
COM3	0.584	0.562	0.461	0.082	0.115	0.12	0.699	0.708	0.727	0.691	0.615	0.736	0.834	1				
COM4	0.513	0.496	0.456	0.021	0.03	0.106	0.537	0.543	0.523	0.53	0.456	0.585	0.569	0.615	1			
COM5	0.407	0.451	0.359	0.035	0.049	0.121	0.469	0.504	0.464	0.459	0.392	0.498	0.533	0.6	0.659	1		
JP1	0.362	0.41	0.215	0.163	0.203	0.16	0.303	0.317	0.386	0.405	0.308	0.348	0.392	0.348	0.197	0.269	1	
JP2	0.201	0.23	0.113	0.073	0.08	0.044	0.207	0.18	0.243	0.238	0.181	0.232	0.28	0.245	0.065	0.1	0.549	1
JP3	0.148	0.139	0.034	0.044	0.069	0.022	0.134	0.158	0.24	0.205	0.169	0.154	0.223	0.169	0.022	0.056	0.526	0.678
JP4	0.119	0.175	0.031	0.03	0.069	0.021	0.159	0.166	0.185	0.176	0.168	0.164	0.214	0.164	0.032	0.085	0.445	0.634
JP5	0.154	0.144	0.05	-0.033	-0.002	-0.016	0.126	0.17	0.214	0.238	0.171	0.137	0.215	0.215	0.077	0.062	0.398	0.492
JP6	0.156	0.144	0.026	0.025	0.067	-0.011	0.083	0.097	0.198	0.181	0.125	0.178	0.195	0.209	0.052	0.085	0.452	0.514
JP7	0.151	0.186	0.061	0.035	0.024	0.014	0.174	0.153	0.18	0.206	0.153	0.204	0.18	0.167	0.106	0.131	0.392	0.524
JP8	0.284	0.268	0.166	0.031	0.049	0.073	0.234	0.23	0.301	0.269	0.185	0.236	0.298	0.268	0.115	0.125	0.45	0.543
JP9	0.199	0.243	0.109	-0.046	0.025	-0.005	0.223	0.223	0.231	0.228	0.17	0.196	0.24	0.203	0.128	0.141	0.415	0.479
MD*LD	-0.303	-0.331	-0.304	-0.365	-0.369	-0.335	-0.276	-0.256	-0.197	-0.216	-0.197	-0.246	-0.239	-0.221	-0.198	-0.149	-0.163	0.013
MD*LE	-0.338	-0.287	-0.309	-0.312	-0.32	-0.304	-0.238	-0.203	-0.161	-0.171	-0.162	-0.186	-0.219	-0.183	-0.169	-0.133	-0.134	0.029
MD*LM	-0.332	-0.331	-0.221	-0.409	-0.42	-0.316	-0.283	-0.273	-0.198	-0.234	-0.218	-0.278	-0.291	-0.257	-0.224	-0.19	-0.152	-0.012
ME*LD	-0.332	-0.377	-0.355	-0.343	-0.431	-0.351	-0.317	-0.301	-0.236	-0.271	-0.231	-0.261	-0.261	-0.258	-0.197	-0.162	-0.184	-0.023
ME*LE	-0.38	-0.343	-0.369	-0.293	-0.39	-0.325	-0.291	-0.269	-0.226	-0.244	-0.214	-0.229	-0.251	-0.247	-0.179	-0.16	-0.155	-0.006
ME*LM	-0.385	-0.398	-0.272	-0.388	-0.496	-0.353	-0.32	-0.336	-0.257	-0.278	-0.265	-0.29	-0.311	-0.286	-0.239	-0.235	-0.171	-0.025
MM*LD	-0.393	-0.394	-0.385	-0.334	-0.376	-0.449	-0.321	-0.316	-0.261	-0.267	-0.257	-0.275	-0.269	-0.253	-0.254	-0.196	-0.159	-0.007
MM*LE	-0.4	-0.35	-0.377	-0.301	-0.352	-0.431	-0.275	-0.276	-0.237	-0.229	-0.223	-0.231	-0.255	-0.23	-0.212	-0.173	-0.149	-0.021
MM*LM	-0.401	-0.387	-0.37	-0.301	-0.364	-0.543	-0.276	-0.303	-0.254	-0.239	-0.255	-0.256	-0.282	-0.237	-0.267	-0.221	-0.109	0.014

Table 7.4: Indicator Correlation Matrix (Continued)

	JP3	JP4	JP5	JP6	JP7	JP8	JP9	MD*LD	MD*LE	MD*LM	ME*LD	ME*LE	ME*LM	MM*LD	MM*LE	MM*LM
JP3	1															
JP4	0.57	1														
JP5	0.508	0.458	1													
JP6	0.526	0.48	0.526	1												
JP7	0.526	0.494	0.487	0.576	1											
JP8	0.498	0.481	0.461	0.466	0.478	1										
JP9	0.49	0.507	0.468	0.549	0.639	0.505	1									
MD*LD	0.036	0.028	0.041	0.053	0.003	-0.019	-0.019	1								
MD*LE	0.051	0.052	0.058	0.066	0.028	-0.004	0.007	0.9	1							
MD*LM	0.041	0.038	0.062	0.046	0.015	-0.02	-0.014	0.815	0.776	1						
ME*LD	0.011	-0.015	-0.015	0.023	-0.013	-0.066	-0.065	0.89	0.814	0.763	1					
ME*LE	0.04	0.024	0.012	0.038	0.027	-0.036	-0.031	0.802	0.877	0.724	0.924	1				
ME*LM	0.028	0.021	0.002	0.028	0.009	-0.037	-0.061	0.757	0.728	0.896	0.846	0.83	1			
MM*LD	0.04	0.013	0.018	0.067	-0.025	-0.068	-0.002	0.754	0.698	0.676	0.767	0.707	0.7	1		
MM*LE	0.04	0.041	0.027	0.073	0.014	-0.038	0.037	0.702	0.75	0.648	0.722	0.777	0.703	0.91	1	
MM*LM	0.091	0.035	0.021	0.066	0.02	-0.025	0.033	0.618	0.586	0.693	0.644	0.63	0.736	0.818	0.813	1

model are sufficiently valid and reliable. This is done with a confirmatory factor analysis and various related techniques. The structural model is used to analyze the relationship among the latent variables in the theoretical model (Chin, 1998; Kock, 2015a).

Measurement Model

The measurement model's latent variables are tested for validity and reliability. The structure matrix of Pearson correlations between indicators and latent variables was obtained through a confirmatory factor analysis that uses principal components as the means of extraction (Chin, 1998), and subsequently transformed by using an oblique (Promax) rotation to obtain the cross-loadings (Kock, 2011, 2015a). This form of rotation is arguably better suited than an orthogonal rotation in models where the correlations among latent variables are expected or theorized (Kline, 2005; Schumacker & Lomax, 2004). The loadings of the indicators to their corresponding latent variables are unrotated (Kock, 2015a).

The confirmatory factor analysis ensures that the latent variables conform to acceptable discriminant and convergent validity criteria. The criterion for convergent validity is that the indicators have a loading equal to or greater than 0.5 on their corresponding latent variable, while their cross-loadings should be less than 0.5 on all other latent variables (Hair, 1992; Kock, 2014). These loadings should be statistically significant at the 5% level ($P<0.05$) (Bagozzi & Yi, 1988; Fornell & Larcker, 1981). The loadings, cross-loadings, and statistical significance (P-values) for the latent variables of the first-order model are shown in Table 7.5, and those of the second-order model are shown in Table 7.6.

There were no items in the latent variables of either the first-order model or the second-order model that needed to be removed because of inadequate loading values (Kock, 2015a). All of the factors loadings in both models are significant at the $P<0.001$ level. The loadings varied from 0.59 to 0.882 for the first-order model as can be seen on Table 7.5.

Table 7.5: Loading and cross-loadings – first-order model

	LD	LE	LM	MD	ME	MM	Type	SE	P value
LD1	0.802	-0.143	-0.25	0.109	-0.105	0.009	Reflect	0.047	<0.001
LD2	0.869	-0.299	-0.072	0.027	-0.037	0.022	Reflect	0.046	<0.001
LD3	0.836	-0.135	-0.228	-0.025	0.038	-0.036	Reflect	0.047	<0.001
LD4	0.876	-0.283	-0.039	-0.078	0.028	-0.014	Reflect	0.046	<0.001
LD5	0.833	-0.214	0.029	0.05	-0.076	0.037	Reflect	0.047	<0.001
LD6	0.882	-0.025	-0.126	-0.142	0.105	0.046	Reflect	0.046	<0.001
LD7	0.738	0.031	-0.11	-0.21	0.218	-0.059	Reflect	0.047	<0.001
LD8	0.814	0.026	-0.097	-0.1	0.157	0.044	Reflect	0.047	<0.001
LD9	0.812	-0.093	0.107	0.017	-0.003	-0.015	Reflect	0.047	<0.001
LD10	0.687	0.196	0.401	0.035	0.124	-0.167	Reflect	0.048	<0.001
LE1	-0.275	0.795	-0.248	0.142	-0.204	-0.027	Reflect	0.047	<0.001
LE2	-0.057	0.816	-0.22	0.038	-0.099	0.067	Reflect	0.047	<0.001
LE3	-0.201	0.851	0	-0.017	-0.053	0.003	Reflect	0.047	<0.001
LE4	-0.079	0.857	-0.057	-0.07	0.026	0.052	Reflect	0.047	<0.001
LE5	0.002	0.849	0.136	0.041	-0.059	-0.068	Reflect	0.047	<0.001
LE6	-0.162	0.622	-0.121	-0.076	0.141	-0.008	Reflect	0.048	<0.001
LM1	-0.042	0.144	0.817	0.048	-0.03	-0.026	Reflect	0.047	<0.001
LM2	0.007	0.466	0.709	0.055	-0.097	0.03	Reflect	0.048	<0.001
LM3	-0.032	0	0.829	-0.083	0.051	0.034	Reflect	0.047	<0.001
LM4	-0.036	-0.044	0.845	0.02	-0.004	-0.004	Reflect	0.047	<0.001
LM5	0.212	-0.363	0.779	0.057	-0.075	-0.079	Reflect	0.047	<0.001
LM6	-0.081	-0.207	0.775	0.018	-0.071	-0.037	Reflect	0.047	<0.001
LM7	0.079	-0.155	0.819	-0.04	0.033	-0.039	Reflect	0.047	<0.001
LM8	-0.614	0.095	0.614	-0.223	0.285	-0.008	Reflect	0.048	<0.001
MD1	-0.173	0.322	-0.161	0.776	-0.723	-0.004	Reflect	0.047	<0.001
MD2	0.035	-0.002	-0.085	0.817	-0.542	-0.099	Reflect	0.047	<0.001
MD3	0.219	-0.199	0.024	0.837	-0.484	-0.144	Reflect	0.047	<0.001
MD4	-0.002	0.046	-0.081	0.843	-0.211	0.055	Reflect	0.047	<0.001
MD5	-0.005	0.073	0.034	0.72	-0.27	0.081	Reflect	0.047	<0.001
MD6	-0.025	0.053	-0.039	0.861	-0.07	-0.086	Reflect	0.047	<0.001
MD7	0.186	-0.191	-0.023	0.667	0.894	-0.184	Reflect	0.048	<0.001
MD8	-0.103	0.067	0.055	0.794	0.033	-0.005	Reflect	0.047	<0.001
MD9	-0.046	-0.05	0.238	0.64	0.44	-0.017	Reflect	0.048	<0.001
MD10	-0.127	0.007	0.18	0.691	0.031	0.046	Reflect	0.048	<0.001
ME1	-0.009	-0.02	0.007	-0.228	0.837	-0.244	Reflect	0.047	<0.001
ME2	0.146	-0.117	-0.034	-0.047	0.821	-0.202	Reflect	0.047	<0.001
ME3	-0.142	0.107	0.004	-0.446	0.782	0.028	Reflect	0.047	<0.001
ME4	0	-0.024	0.089	-0.157	0.744	-0.08	Reflect	0.047	<0.001
ME5	-0.193	0.228	-0.019	-0.314	0.77	0.136	Reflect	0.047	<0.001
ME6	0.358	-0.426	-0.067	0.151	0.758	-0.04	Reflect	0.047	<0.001
MM1	-0.078	0.144	-0.086	-0.064	0.188	0.691	Reflect	0.048	<0.001
MM2	0.084	-0.148	0.021	0.268	0.176	0.574	Reflect	0.048	<0.001
MM3	-0.132	0.167	-0.051	-0.057	-0.054	0.856	Reflect	0.047	<0.001
MM4	-0.199	0.167	-0.05	0.007	-0.032	0.821	Reflect	0.047	<0.001
MM5	0.331	-0.519	0.193	0.122	-0.388	0.59	Reflect	0.048	<0.001
MM6	0.271	-0.361	0.118	0.043	-0.325	0.662	Reflect	0.048	<0.001
MM7	-0.076	0.184	-0.111	-0.057	-0.143	0.786	Reflect	0.047	<0.001
MM8	-0.217	0.174	-0.044	-0.074	0.013	0.63	Reflect	0.048	<0.001

Notes: First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning-making dimension.

The loadings varied from 0.64 to 0.915 for the second-order model, as can be seen on Table 7.6. The loadings show that the measurement instrument has acceptable convergent validity (Hair et al., 2011; Kock, 2015a).

Table 7.6: Loadings and cross loadings – second-order model

	ML	MN	SAT	COM	PERF	MN*ML	Type	SE	P value
LD	0.964	-0.001	-0.064	-0.061	-0.014	-0.02	Formative	0.046	<0.001
LE	0.864	0.102	-0.084	0.002	0.029	0.013	Formative	0.047	<0.001
LM	0.756	-0.063	-0.192	-0.091	-0.057	-0.034	Formative	0.047	<0.001
MD	-0.251	0.878	-0.003	0.137	-0.004	-0.037	Formative	0.046	<0.001
ME	-0.214	0.922	0.138	-0.012	0.017	-0.101	Formative	0.046	<0.001
MM	0.334	0.693	-0.008	-0.222	-0.071	-0.047	Formative	0.048	<0.001
SAT1	-0.149	0.039	0.916	-0.109	-0.035	-0.016	Reflective	0.046	<0.001
SAT2	-0.074	-0.013	0.915	-0.092	-0.058	-0.022	Reflective	0.046	<0.001
SAT3	-0.015	-0.048	0.9	-0.044	0.029	0.031	Reflective	0.046	<0.001
SAT4	-0.194	0.071	0.917	-0.067	0.036	0.04	Reflective	0.046	<0.001
SAT5	0.027	0.041	0.799	-0.221	0.002	0.074	Reflective	0.047	<0.001
COM1	-0.092	-0.01	0.408	0.827	-0.014	-0.016	Reflective	0.047	<0.001
COM2	-0.056	-0.022	0.311	0.887	0.049	-0.021	Reflective	0.046	<0.001
COM3	-0.12	-0.026	-0.03	0.924	0.023	-0.001	Reflective	0.046	<0.001
COM4	0.079	-0.055	-0.618	0.752	-0.12	0.023	Reflective	0.047	<0.001
COM5	-0.046	-0.022	-0.747	0.686	-0.087	0.019	Reflective	0.048	<0.001
JP1	0.146	0.04	-0.021	0.056	0.64	-0.101	Reflective	0.048	<0.001
JP2	0.058	-0.046	-0.135	0.061	0.774	-0.04	Reflective	0.047	<0.001
JP3	-0.016	-0.03	0.077	-0.157	0.767	-0.007	Reflective	0.047	<0.001
JP4	-0.09	-0.013	0.059	-0.078	0.701	-0.007	Reflective	0.048	<0.001
JP5	-0.097	-0.103	0.074	-0.048	0.678	-0.034	Reflective	0.048	<0.001
JP6	0.02	-0.033	-0.3	0.209	0.725	0.017	Reflective	0.047	<0.001
JP7	-0.06	-0.005	-0.107	0.074	0.724	-0.011	Reflective	0.047	<0.001
JP8	0.236	-0.077	-0.114	-0.04	0.691	-0.041	Reflective	0.048	<0.001
JP9	-0.044	-0.092	0.02	-0.029	0.722	-0.053	Reflective	0.047	<0.001
MD*LD	0.081	-0.022	-0.037	-0.017	0	0.9	Reflective	0.046	<0.001
MD*LE	-0.074	0.053	0.066	0.033	0.023	0.888	Reflective	0.046	<0.001
MD*LM	0.169	-0.097	0.059	-0.252	0.032	0.858	Reflective	0.047	<0.001
ME*LD	0.078	-0.046	-0.168	0.088	-0.058	0.915	Reflective	0.046	<0.001
ME*LE	-0.067	0.024	-0.083	0.116	-0.009	0.903	Reflective	0.046	<0.001
ME*LM	0.124	-0.126	-0.048	-0.145	0.002	0.882	Reflective	0.046	<0.001
MM*LD	-0.166	-0.06	-0.053	0.089	0.026	0.855	Reflective	0.047	<0.001
MM*LE	-0.252	-0.002	0.017	0.121	0.045	0.861	Reflective	0.047	<0.001
MM*LM	-0.22	-0.131	0.06	-0.015	0.092	0.783	Reflective	0.047	<0.001

Notes: First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning-making dimension. Thus, LM is the score of motivating language's meaning-making dimension, and MM is the is the degree of media naturalness used when communicating the meaning-making dimension. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*). Loadings are shaded grey and cross loadings are not shaded.

Discriminant Validity is tested by comparing the inter-construct correlations with the square root of the average variance extracted (AVE) of each variable. Tables 7.7 and 7.8 show the square root of the AVEs for the variables shaded in the diagonal, and the inter-construct correlations for the first-order and second-order model, respectively. When comparing the square root of the AVEs to the other values in the column (correlations), the square root of the AVE should be greater than all the correlations in the column. Since the above conditions were met, the results of this test indicate that the discriminant validity of the latent variables is satisfactory for both models (Fornell & Larcker, 1981; Kock, 2015a).

Table 7.7: Correlation among the latent variables and the square root of the average variance extracted (AVE) – first-order model

	LD	LE	LM	MD	ME	MM
LD	0.817					
LE	0.853	0.803				
LM	0.722	0.699	0.777			
MD	0.169	0.222	0.027	0.768		
ME	0.216	0.284	0.051	0.853	0.786	
MM	0.331	0.351	0.317	0.588	0.646	0.708

Notes: The square roots of the average variance extracted (AVEs) are shaded grey in the diagonal. The correlations among variables are not shaded. First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates meaning-making dimension. Thus, LM is the score of motivating language's meaning-making dimension, and MM is the degree of media naturalness used when communicating the meaning-making dimension.

Table 7.8: Correlations between the latent variables and the square root of the AVEs for the second-order model

	ML	MN	SAT	COM	JP	MN*ML
ML	0.866					
MN	0.251	0.837				
SAT	0.75	0.17	0.891			
COM	0.737	0.158	0.871	0.82		
JP	0.304	0.105	0.338	0.331	0.715	
MN*ML	-0.347	-0.338	-0.292	-0.284	0.006	0.873

Notes: The square roots of the Average Variance Extracted (AVEs) are shaded grey in the diagonal. The correlations among variables are not shaded. ML = motivating language. MN = media naturalness. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*).

Measurement reliability has traditionally been assessed using composite reliability (CR) or Cronbach's alpha (CA) based tests. The CA provides an estimate of the indicator intercorrelations (Henseler et al.), and an acceptable measure is 0.7 or higher (Nunnally & Bernstein, 1994). Another measure of reliability is CR that should have a score of 0.7 or greater in order for the measure to be reliable (Hair, 1992; Nunnally & Bernstein, 1994). The CR takes into account the scores loadings unlike CA, thus its use is recommended when using PLS (Hair et al., 2011). A score of 0.7 or above is considered an indicator that a latent variable has acceptable reliability (Kock & Mayfield, 2015; Nunnally & Bernstein, 1994). Table 7.9 shows that the threshold values are exceeded for the first-order model, and Table 7.10 shows the same for the second-order model.

Table 7.9: Latent Variable Coefficients for the first-order model

	LD	LE	LM	MD	ME	MM
R-Squared						
Composite Reliability	0.952	0.915	0.924	0.934	0.906	0.888
Cronbach's alpha	0.952	0.914	0.921	0.932	0.905	0.88
Average Variance Extracted	0.668	0.644	0.604	0.59	0.618	0.502
Q-squared						

First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning-making dimension. Thus, LM is the score of motivating language's meaning-making dimension, and MM is the degree of media naturalness used when communicating the meaning-making dimension.

Table 7.10: Latent Variable Coefficients for the second-order model

	ML	MN	SAT	JP	OC	MN*ML
R-Squared		0.132	0.56	0.226	0.541	
Composite Reliability	0.899	0.873	0.95	0.904	0.91	0.966
Cronbach's alpha	0.904	0.873	0.945	0.902	0.898	0.966
Average Variance Extracted	0.749	0.7	0.793	0.511	0.672	0.761
Q-squared		0.136	0.562	0.248	0.544	

ML = motivating language. MN = media naturalness. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*).

A full collinearity test was performed to examine the existence of multicollinearity among the latent variables. This is done by calculating the variance inflation factors (VIFs) for each for each latent variable in relation to the rest of the latent variables in the model (Kline, 2005). The full collinearity VIFs are calculated automatically for all the variables by WarpPLS 6.0 (Kock, 2015a). The test for both models finds no multicollinearity issues, since all the values are below the acceptable threshold of five, as seen on Table 7.11 for the first-order model and Table 7.12 for the second-order model (Hair et al., 2011; Kline, 2005).

Table 7.11: Full collinearity Variance Inflation Factors for the first-order model

LD	4.152
LE	4.141
LM	2.513
MD	3.715
ME	4.384
MM	2.024

First Letter: "L" indicates a motivating language indicator; M indicates media naturalness is being measured at the ML indicator. Second Letter: "D" indicates the direction giving dimension; "E" indicates the empathetic language dimension; "M" indicates the meaning-making dimension. Thus, LM is the score of motivating language's meaning-making dimension, and MM is the degree of media naturalness used when communicating the meaning-making dimension.

Table 7.12: Full collinearity Variance Inflation Factors for the second-order model

ML	2.79
MN	1.306
SAT	4.695
JP	1.279
OC	4.602
EXP	1.776
TENURE	1.404
ED	1.186
GDR	1.216
MN*ML	1.313

ML = motivating language. MN = media naturalness. SAT = job satisfaction. JP = job performance. COM = organizational commitment. The loadings for the moderating effect of MN on ML are the interaction effects as indicated by the multiplication sign (*). EXP = experience, AHI = Annual Household Income. ED = education. GDR = gender.

Table 7.13 shows the indicator weights for the first -order models as well as the standard error, P value, VIF, weight loading sign (WLS), and effect size (ES). The WLS should have a value of one to indicate the absence of Simpson's Paradox, and therefore possible model misspecification (Kock & Gaskins, 2016).

Ideally, the VIF values should be no greater than 2.5 for indicators of formative variables (Hair et al., 2011; Kock, 2015a), and values above this threshold indicate that they may warrant a merger of the offending indicators (Hair et al., 2011). However, this merger would contradict the theoretical foundations of the MLT. For this reason, we proceed with caution with the research.

Table 7.14 shows the indicator weights for the second-order models as well as the standard error, P value, VIF, weight loading sign (WLS), and effect size (ES).

Structural Model

The model fit is evaluated by using the average path coefficients (APC), average R-squared (ARS), and the average variance inflation factor (AVIF). The research recommends that the first two be at least 0.05, while the AVIF should be lower than 5 (Hair, 1992; Kline, 2005; Kock & Mayfield, 2015). Table 7.15 shows that these results are acceptable according to the above criteria and that the data is a good fit with the second-order model. The model fit indices are not reported for the first-order model, since it is used solely to convert the first-order latent variables LD, LE, LM, MD, ME, and MM into usable indicators so that they can be used to create the second-order latent variables ML and MN.

Results

Figure 7.1 shows the results for the analyses of the SEM model and the hypotheses. Each hypothesis is represented in the model as either a link between two latent variables, or a link that moderates a relationship between two latent variables with the exception of the control variables to the right hand of job performance. The latent variables of interest are represented by ovals. ML and MN are formative, while job satisfaction, job performance, and organizational

Table 7.13: Indicator weights for the first-order model

	LD	LE	LM	MD	ME	MM	Type	SE	P value	VIF	WLS	ES
LD1	0.1						Reflective	0.052	0.027	3.28	1	0.08
LD2	0.144						Reflective	0.052	0.003	4.302	1	0.125
LD3	0.115						Reflective	0.052	0.014	3.486	1	0.096
LD4	0.146						Reflective	0.052	0.002	3.915	1	0.128
LD5	0.13						Reflective	0.052	0.006	3.253	1	0.108
LD6	0.165						Reflective	0.051	<0.001	3.971	1	0.145
LD7	0.067						Reflective	0.052	0.098	2.223	1	0.05
LD8	0.116						Reflective	0.052	0.013	2.899	1	0.095
LD9	0.112						Reflective	0.052	0.016	2.828	1	0.091
LD10	0.053						Reflective	0.052	0.155	1.855	1	0.036
LE1		0.187					Reflective	0.051	<0.001	2.622	1	0.149
LE2		0.208					Reflective	0.051	<0.001	2.882	1	0.17
LE3		0.213					Reflective	0.051	<0.001	2.93	1	0.181
LE4		0.237					Reflective	0.051	<0.001	3.171	1	0.203
LE5		0.192					Reflective	0.051	<0.001	3.128	1	0.163
LE6		0.084					Reflective	0.052	0.053	1.666	1	0.052
LM1			0.165				Reflective	0.051	<0.001	2.626	1	0.135
LM2			0.086				Reflective	0.052	0.05	2.024	1	0.061
LM3			0.183				Reflective	0.051	<0.001	3.402	1	0.152
LM4			0.194				Reflective	0.051	<0.001	3.421	1	0.164
LM5			0.146				Reflective	0.052	0.002	3.201	1	0.114
LM6			0.155				Reflective	0.051	0.001	3.189	1	0.12
LM7			0.17				Reflective	0.051	<0.001	2.822	1	0.139
LM8			0.068				Reflective	0.052	0.096	1.621	1	0.042
MD1				0.085			Reflective	0.052	0.051	3.476	1	0.066
MD2				0.165			Reflective	0.051	<0.001	4.637	1	0.135
MD3				0.146			Reflective	0.052	0.002	4.493	1	0.122
MD4				0.161			Reflective	0.051	<0.001	3.124	1	0.136
MD5				0.1			Reflective	0.052	0.027	2.19	1	0.072
MD6				0.174			Reflective	0.051	<0.001	3.652	1	0.149
MD7				0.072			Reflective	0.052	0.083	1.819	1	0.048
MD8				0.129			Reflective	0.052	0.006	3.057	1	0.103
MD9				0.071			Reflective	0.052	0.086	1.782	1	0.046
MD10				0.089			Reflective	0.052	0.044	2.123	1	0.061
ME1					0.263		Reflective	0.051	<0.001	3.026	1	0.221
ME2					0.224		Reflective	0.051	<0.001	2.975	1	0.184
ME3					0.188		Reflective	0.051	<0.001	2.308	1	0.147
ME4					0.16		Reflective	0.051	0.001	2.145	1	0.119
ME5					0.17		Reflective	0.051	<0.001	2.251	1	0.131
ME6					0.141		Reflective	0.052	0.003	2.142	1	0.107
MM1						0.149	Reflective	0.052	0.002	1.95	1	0.103
MM2						0.078	Reflective	0.052	0.066	1.558	1	0.045
MM3						0.259	Reflective	0.051	<0.001	3.951	1	0.222
MM4						0.21	Reflective	0.051	<0.001	3.239	1	0.172
MM5						0.123	Reflective	0.052	0.009	2.294	1	0.073
MM6						0.122	Reflective	0.052	0.009	2.561	1	0.081
MM7						0.166	Reflective	0.051	<0.001	2.666	1	0.13
MM8						0.116	Reflective	0.052	0.013	1.769	1	0.073

commitment are reflective in nature. The latent variables are reduced to individual scores by using the factor-based PLS Type CFM1 outer model analysis algorithm, since it "generates estimates of both true composites and factors, in two stages, explicitly accounting for measurement error" (Kock, 2015c, p. 22). Thus the latent variables are composed of true factors and not as linear combinations of indicators (Kock, 2015a, 2015b), which has been a perceived limitation of Wold's PLS algorithms (Kock, 2015c).

Table 7.14: Indicator weights for the second-order model

	ML	MN	SAT	COM	PERF	MN*ML	Type (a	SE	P value	VIF	WLS	ES
LD	0.683						Formative	0.048	<0.001	4.148	1	0.659
LE	0.119						Formative	0.052	0.011	3.885	1	0.103
LM	0.152						Formative	0.051	0.002	2.206	1	0.115
MD		0.243					Formative	0.051	<0.001	3.695	1	0.214
ME		0.54					Formative	0.049	<0.001	4.148	1	0.498
MM		0.166					Formative	0.051	<0.001	1.73	1	0.115
SAT1			0.285				Reflective	0.051	<0.001	4.461	1	0.261
SAT2			0.271				Reflective	0.051	<0.001	4.539	1	0.248
SAT3			0.174				Reflective	0.051	<0.001	3.966	1	0.156
SAT4			0.213				Reflective	0.051	<0.001	4.542	1	0.195
SAT5			0.087				Reflective	0.052	0.048	2.499	1	0.069
COM1				0.165			Reflective	0.051	<0.001	2.692	1	0.137
COM2				0.233			Reflective	0.051	<0.001	3.862	1	0.207
COM3				0.365			Reflective	0.05	<0.001	3.993	1	0.337
COM4				0.187			Reflective	0.051	<0.001	2.15	1	0.141
COM5				0.103			Reflective	0.052	0.024	1.984	1	0.071
JP1					0.115		Reflective	0.052	0.013	1.622	1	0.074
JP2					0.184		Reflective	0.051	<0.001	2.518	1	0.143
JP3					0.163		Reflective	0.051	<0.001	2.255	1	0.125
JP4					0.128		Reflective	0.052	0.007	1.95	1	0.09
JP5					0.112		Reflective	0.052	0.016	1.674	1	0.076
JP6					0.143		Reflective	0.052	0.003	1.926	1	0.103
JP7					0.144		Reflective	0.052	0.003	2.103	1	0.104
JP8					0.126		Reflective	0.052	0.008	1.719	1	0.087
JP9					0.142		Reflective	0.052	0.003	2.038	1	0.103
MD*LD						0.165	Reflective	0.051	<0.001	23.939	1	0.148
MD*LE						0.064	Reflective	0.052	0.109	22.654	1	0.057
MD*LM						0.094	Reflective	0.052	0.035	9.913	1	0.081
ME*LD						0.093	Reflective	0.052	0.037	39.311	1	0.085
ME*LE						0.144	Reflective	0.052	0.003	39.031	1	0.13
ME*LM						0.18	Reflective	0.051	<0.001	12.581	1	0.159
MM*LD						0.128	Reflective	0.052	0.007	12.085	1	0.11
MM*LE						0.128	Reflective	0.052	0.007	12.656	1	0.11
MM*LM						0.082	Reflective	0.052	0.059	4.378	1	0.064

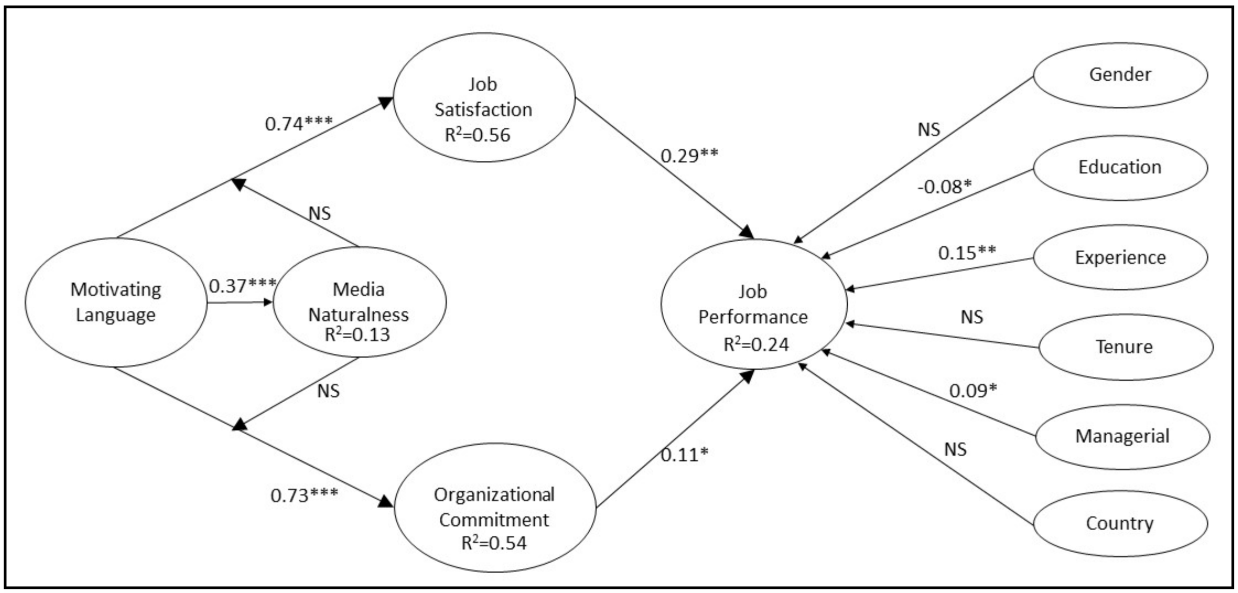
The default algorithm of the inner model is set to Warp3. This algorithm allows the software to find the best fitting curve for the relationships being examined (Kock, 2015c). The resampling method is set to Stable 3, since it is recommended as being the more accurate one (Kock, 2015c). The individual inner model algorithm settings were changed from Warp3 to linear for the link between ML and job satisfaction, and the link between ML and organizational commitment. These changes ensure that the moderating effect of MN on these relationships is not be captured by as a non-linear relationship between ML and job satisfaction or ML and organizational commitment (Kock, 2014, 2015c). The statistical power and sample size are examined by using the explore statistical power and minimum sample size requirements option in WarpPLS 6.0. The software utilizes the minimum statistically significant path coefficient, significance level, and minimum power requirements to calculate the minimum sample size. The minimum significant path coefficient is 0.11, the significance level is 0.05, and the minimum power is 0.8 that dictates a minimum sample size of 353 according to the gamma-exponential method of calculation. Therefore, these values satisfy the requirements for the minimum sample size, significance level, and statistical power requirements (Kock, 2014, 2017).

Table 7.15: Model fit indices for the second-order model

APC	ARS	AVIF
0.210, P<0.001	0.371, P<0.001	1.594

As mentioned earlier, ML is a second-order construct and has been since Sullivan proposed its theoretical framework (Sullivan, 1988). Thus, when the measurement scale for ML was first developed, it was implemented as a second-order latent variable in a SEM (J. Mayfield et al., 1995). Therefore, it logically follows that the measurement of the degree of naturalness that is used in communicating ML should similarly be a second-order latent variable, since MN is measured at the indicator level of ML. Figure 7.2 shows that there are no relationships between the variables, since the purpose of this step is to produce indicators for the second-order model. The algorithm options for WarpPLS 6.0 in the first-order model are the same as for those options specified in the second-order model.

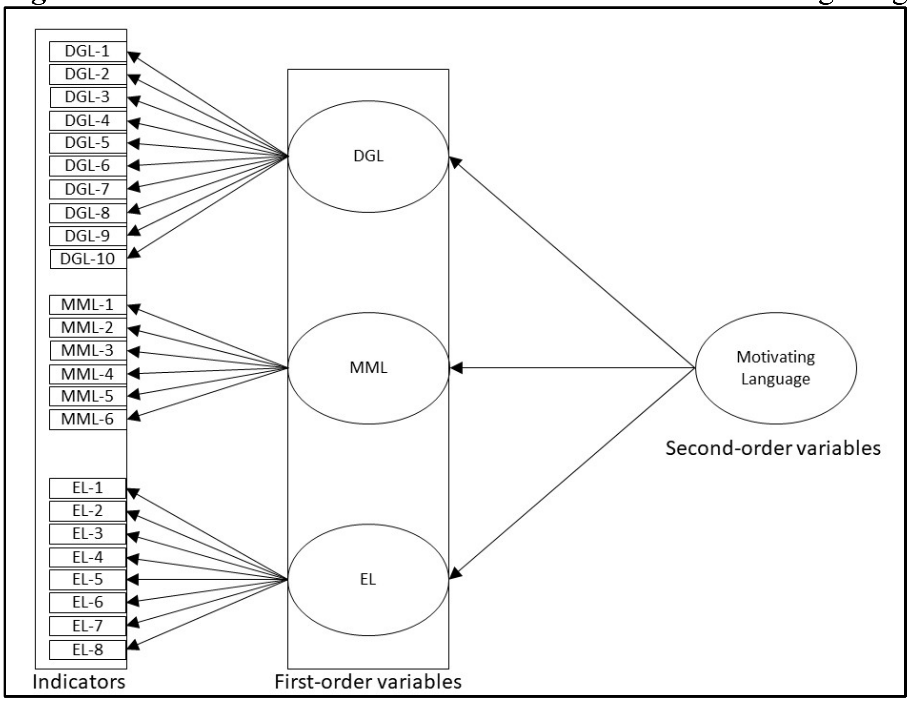
Figure 7.1: Research model with path coefficients and their p-values



(*) P-Value ≤ 0.05; (**) P-Value ≤ 0.01; (***) P-Value < 0.001; Paths with no coefficients are labeled NS

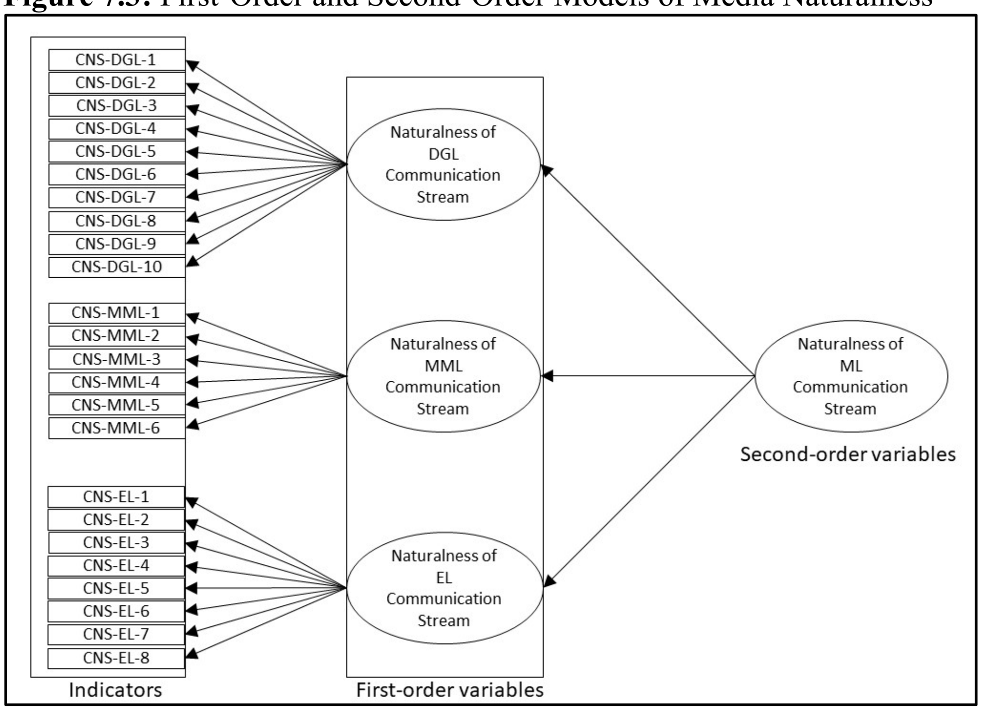
In order to construct ML and MN as second-order latent variables, construction of the three dimensions that compose ML from their respective indicators are needed: DGL, EL, and MML. The measurement scale for ML indicates that the DGL has 10 indicators, the EL has 6 indicators, and the MML has 8 indicators (J. Mayfield et al., 1995). After constructing each of these three dimensions as three latent variables for ML and three latent variables for MN. The next step is to perform the SEM analysis and save the latent variables as standardized indicators (Kock, 2015c). The result is that there are now three that are going to be composed into ML, and another three indicators that will be composed into MN.

Figure 7.2: First-Order and Second-Order Models of Motivating Language



DGL = Direction Giving Language; MML = Meaning Making Language; EL = Empathetic Language

Figure 7.3: First-Order and Second-Order Models of Media Naturalness



DGL = Direction Giving Language; MML = Meaning Making Language; EL = Empathetic Language
"CNS-" = Communication Naturalness Score for the corresponding Motivating Language indicator

The next section of this study will discuss the results of the pilot study.

Results Overview

The main study does not replicate the main findings of the pilot study because the moderating effect of MN on ML that was initially found in the pilot study does not exist in the main study. However, the rest of the results are similar.

Hypothesis 1 proposes an association between a supervisor's use of ML and job satisfaction. A significant association exists that has a path coefficient of 0.74 and a P<0.001. This association indicates that the study finds that the use of ML by a supervisor leads to job satisfaction, which is consistent with previous literature (J. Mayfield & Mayfield, 2007).

Table 7.16: Hypotheses support summary

	Path Coefficient	P Value	Supported?
H1: ML is positively associated with job satisfaction	0.74	P<0.01	Yes
H2: ML is positively associated with organizational commitment	0.73	P<0.01	Yes
H3: Job satisfaction is positively associated with job performance	0.29	P<0.01	Yes
H4: Organizational commitment is positively associated with job performance	0.11	P=0.02	Yes
H5: The association between ML and job satisfaction is moderated by MN used to communicate said language	0.02	P=0.38	No
H6: The association between ML and organizational commitment is moderated by the MN used to communicate said language	0.02	P=0.38	No
H7: The use of ML is positively associated with MN	0.37	P<0.01	Yes

Figure 7.4 presents a visual representation of the positive association between ML and job satisfaction. This relation is manually set to be linear in WarpPLS 6.0 as recommended by Kock (Kock, 2015a), since the presence of moderating variables can be captured by a nonlinear relation.

In a similar manner, Hypothesis 2 proposes an association between a supervisor's use of ML and organizational commitment. A significant association exists that has a path coefficient of

0.74 and a P<0.001. This association indicates that the study finds that the use of ML by a supervisor leads to higher organizational commitment, which is consistent with previous literature (J. Mayfield & Mayfield, 2010; J. Mayfield et al., 1998).

Figure 7.4: Plot of the relationship between Motivating Language and Job Satisfaction

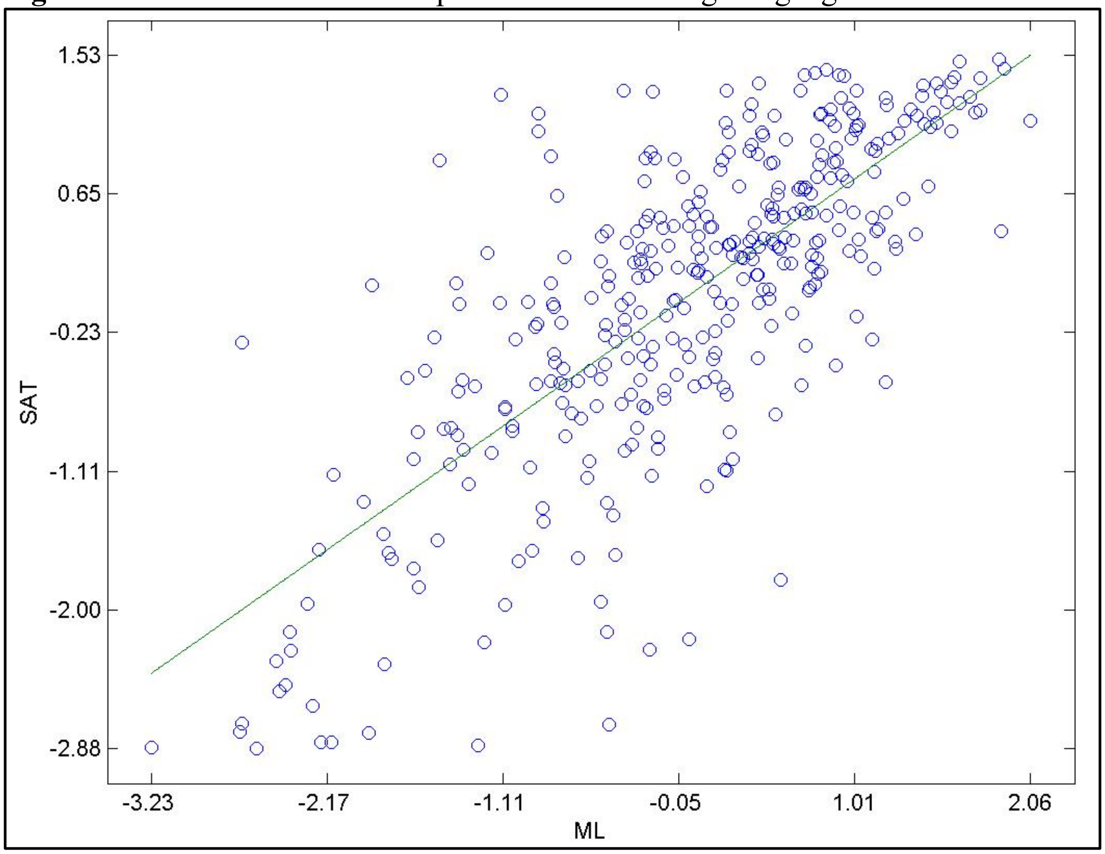


Figure 7.5 presents a visual representation of the positive association between ML and organizational commitment. Once again, this relationship is manually set to be linear in WarpPLS 6.0 as recommended by Kock (Kock, 2015a), since the presence of moderating variables can be captured by a non-linear relationship.

Hypothesis 3 proposes that there is a relationship between job satisfaction and job performance. A significant association exists that has a path coefficient of 0.29 and a P≤0.01.

Thus, the association between the two latent variables is confirmed.

Figure 7.5: Plot of the relationship between ML and organizational commitment

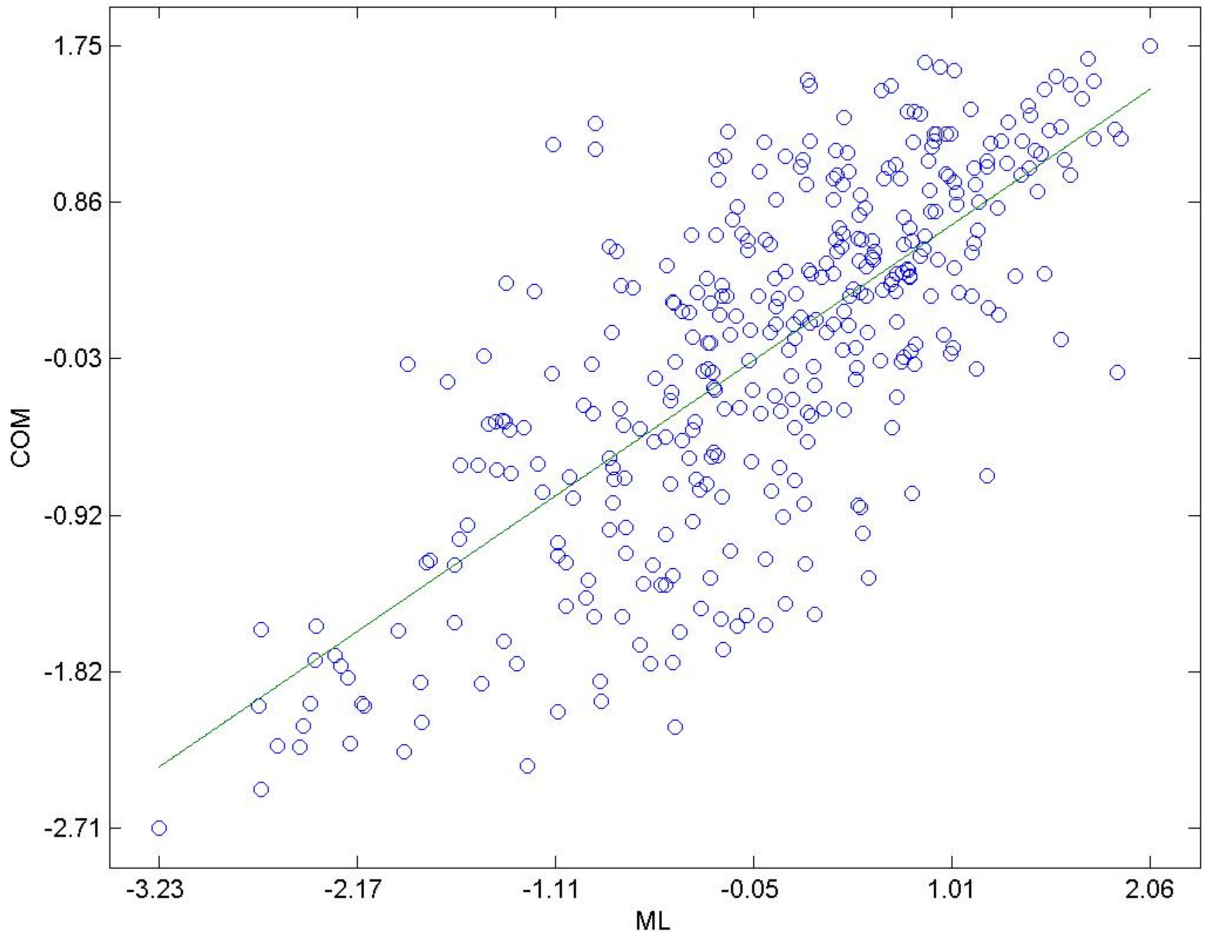


Figure 7.6 shows a plot of the relationship between job satisfaction and job performance. In this case, the relationship is set to Warp 3 in WarpPLS 6.0. This setting means that the relationship will be nonlinear with three slopes and two points of inflection. The path coefficient indicates that greater job satisfaction leads to job performance. Even though the shape of the curve may be counterintuitive, there is the possibility that it is being warped by the presence of hard-working employees who are dissatisfied at their job.

Hypothesis 4 proposes that there is an association between organizational commitment and job performance. A significant association exists that has a path coefficient of 0.11 and a P≤0.05. Thus, the association between the two latent variables is confirmed.

Figure 7.6: Plot of the relationship between job satisfaction and job performance

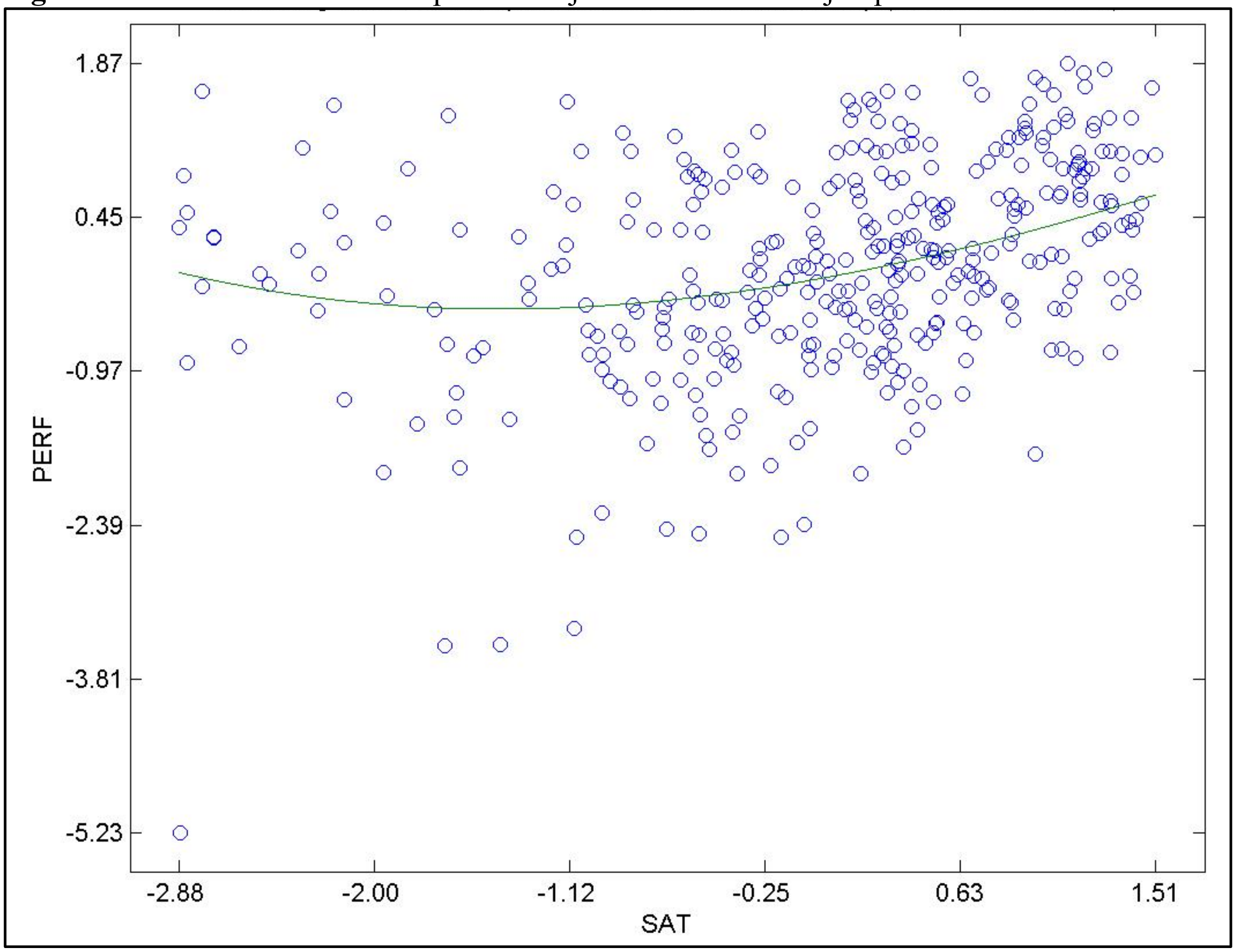


Figure 7.7 shows a plot of the relationship between organizational commitment and job performance. In this case, the relationship is set to Warp 3 in WarpPLS 6.0. This setting means that the relation will be nonlinear with three slopes and two points of inflection. However, it is curved with two slopes and one point of inflection. The path coefficient indicates that greater job satisfaction leads to job performance.

Hypothesis 5 proposes that the relationship between ML and job satisfaction is moderated by MN. This study finds that MN does not moderate this relationship. This moderating effect is non-existent and has a path coefficient of 0.02 and a P=0.38. The results indicate that using a communication medium with a higher degree of naturalness does not influence the effect that ML has on job satisfaction.

Figure 7.8 shows a 3D graph with all three variables where the interaction effect can be seen more clearly.

Figure 7.9 shows a plot where MN is split between high and low levels along its median. The figures show the large area of overlap between the high MN curve and the low MN curves. This overlap clearly indicates that both high and low MN produce similar outcomes for job satisfaction among a large enough proportion of the respondents.

Hypothesis 6 proposes that the relationship between ML and organizational commitment is moderated by MN. Once again, MN does not moderate the effect of ML. This moderating effect of MN on the relation between ML and organizational commitment is in effect non-existent and has a path coefficient of 0.02 and a P=0.38. The results indicate that using a communication medium with a higher degree of naturalness does not influence the effect that ML has on organizational commitment.

Figure 7.10 shows a 3D graph with all three variables where the interaction effect can be seen more clearly.

Figure 7.11 shows a plot where MN is split between high and low levels along its median. They clearly show the large area of overlap between the high MN curve and the low MN curves. This overlap clearly indicates that both high and low MN produce similar outcomes for jobs satisfaction among a large enough proportion of the respondents.

Figure 7.7: Plot of the relationship between organizational commitment and job performance

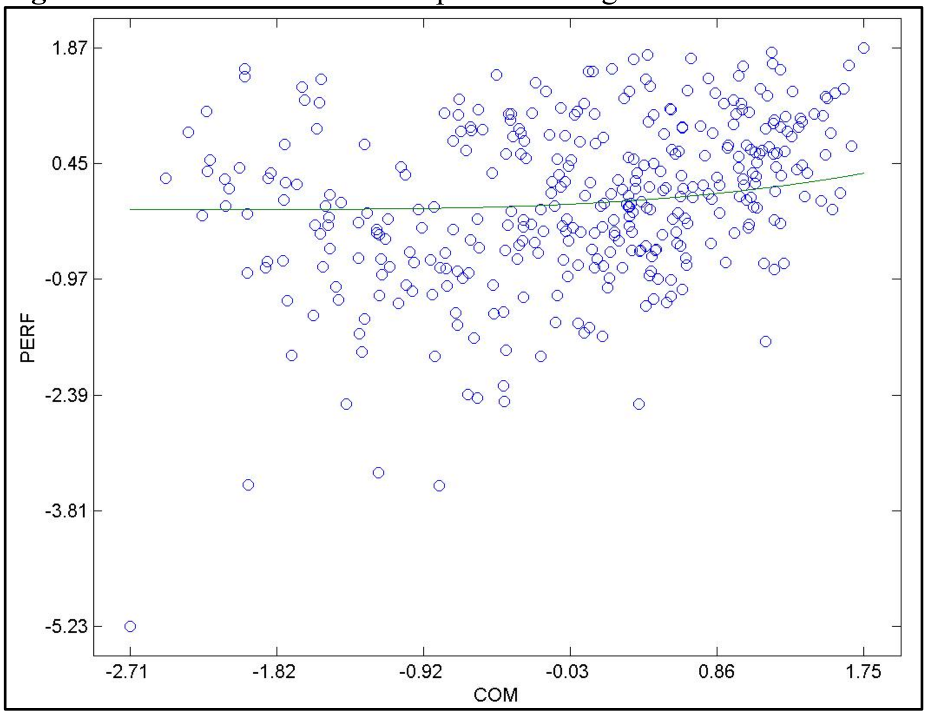


Figure 7.8: Rocky 3D graph denoting the moderating effect of MN on the relationship between ML and job satisfaction (standardized scales)

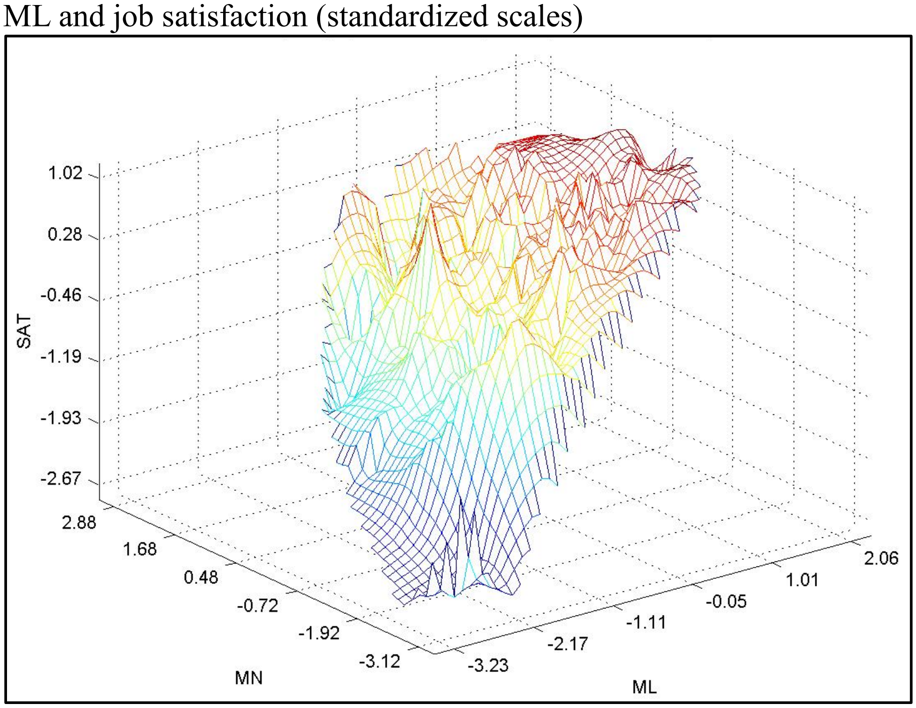


Figure 7.9: Plot graph denoting the moderating effect of high and low levels of MN on the relation between ML and job satisfaction

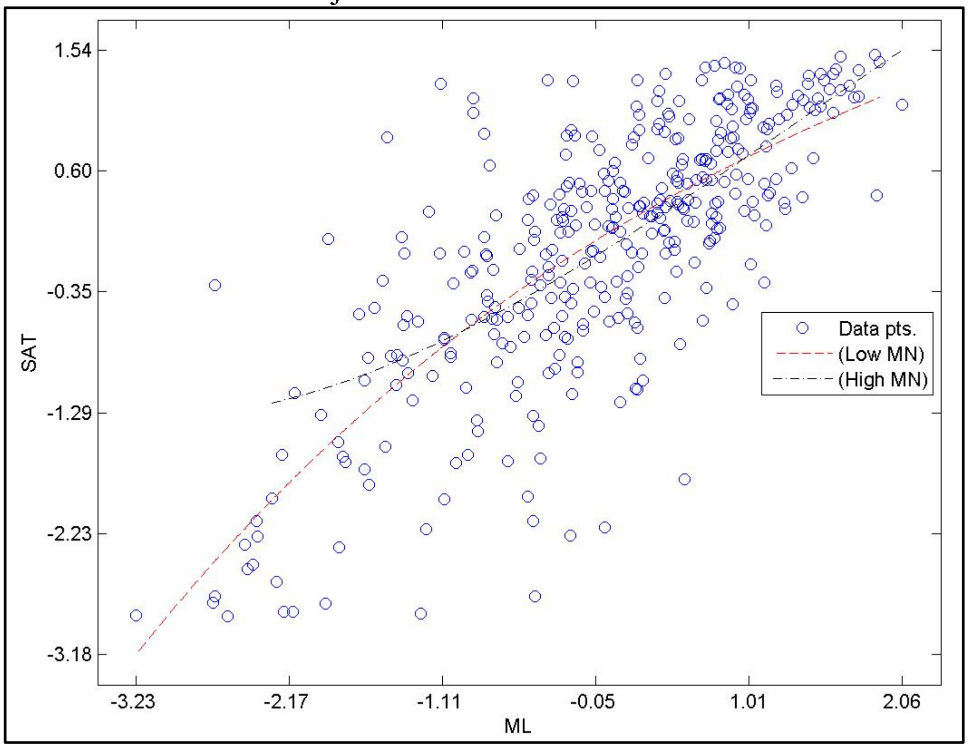
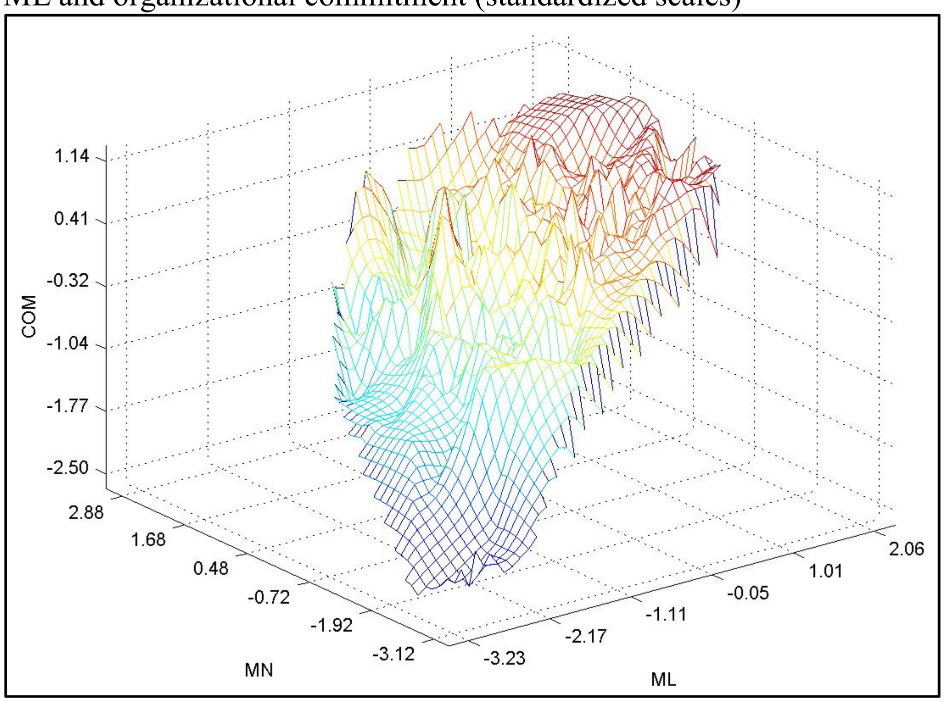


Figure 7.10: Rocky 3D graph denoting the moderating effect of MN on the relationship between ML and organizational commitment (standardized scales)



Hypothesis 7 proposes that ML is associated with MN. As mentioned previously, managers will display a tendency to mix together communication media with a higher degree of naturalness as their use of ML increases. This relationship is positive and significant and so supports the hypothesis. The path coefficient of this relation is 0.37 with a P<0.001.

Figure 7.12 shows a plot of this relationship. In this case, the relationship is set to Warp 3 in WarpPLS 6.0 that means that the relation is nonlinear with three slopes and two points of inflection.

Figure 7.11: Plot graph denoting the moderating effect of high and low levels of MN on the relationship between ML and organizational commitment

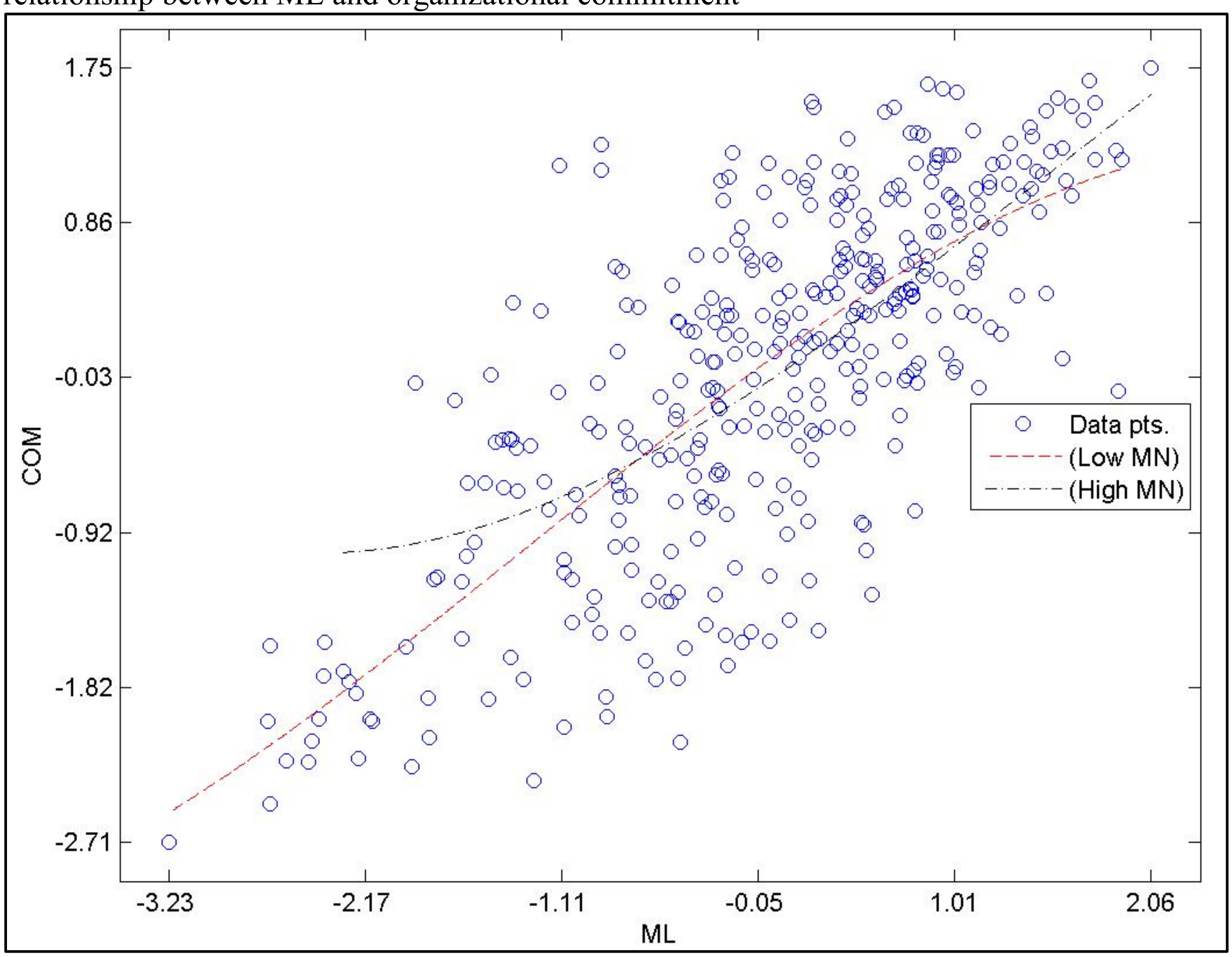
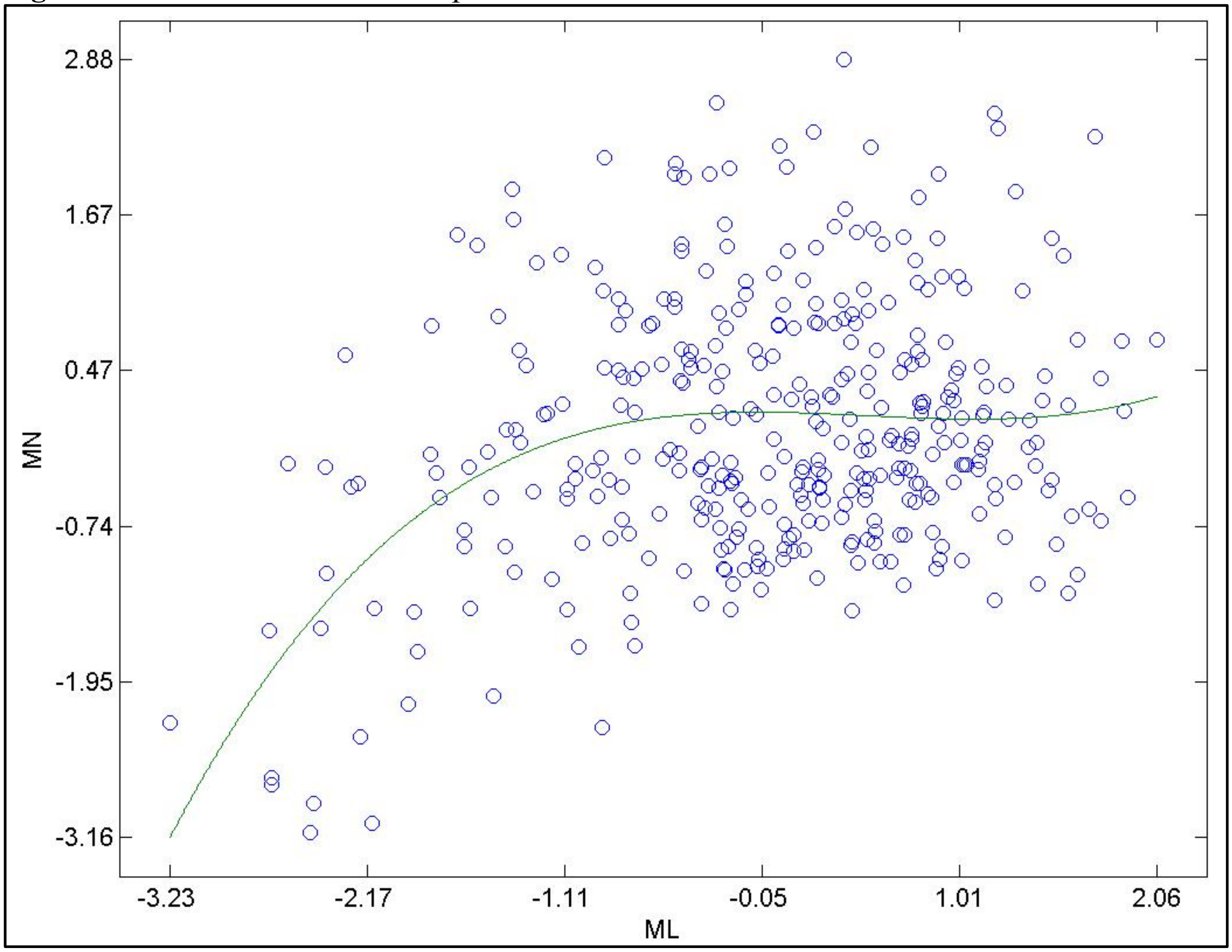


Figure 7.12: Plot of the relationship between ML and MN



Total, Direct, and Indirect Effects

WarpPLS version 6 calculates the indirect and total effects of all the latent variables that are linked by a path with one or more segments. The software provides: "The path coefficients associated with the effects, the number of paths that make up the effects, the P values associated with effects (calculated via resampling, using the selected resampling method), the standard errors associated with the effects, and effect sizes associated with the effects. Indirect effects are aggregated for paths with a certain number of segments" (Kock, 2015a, p. 80). The effect sizes are calculated as Cohen's (Cohen, 2009) f-size threshold.

Table 7.17 shows the total effect for ML, along with the number of paths that are in their calculation, and the size of the effect and P value. The calculations for the total effects automatically account for all of the paths that connect the two variables in question (Kock, 2015a). Table 7.17 shows that all the effects are statistically significant at the P<0.01 level.

The sizes of the effects for job satisfaction and organizational commitment have large magnitudes, while the effects for job performance and MN have small ones. According to Cohen's guidelines, a small effect ranges from 0.02 to less than 0.15; a medium effect ranges from 0.15 to less than 0.35, while a large effect is greater than 0.35 (Cohen, 2009).

Table 7.17: Total effects of ML

	Paths	**Total Effect**	**Effect Size**	**P Value**
SAT	1	0.742	0.557	<0.001
COM	1	0.73	0.538	<0.001
JP	2	0.293	0.089	<0.001
MN	1	0.367	0.135	<0.001

Table 7.18 shows the effects that MN has on job satisfaction, organizational commitment, and job performance through its mediating effect on ML. The magnitude of the effect on these variables is well below the low threshold but is statistically non-significant as well.

Table 7.18: Total effects of MN

	Paths	**Total Effect**	**Effect Size**	**P Value**
SAT	1	-0.016	0.006	Non-Significant
COM	1	-0.016	0.006	Non-Significant
JP	2	-0.006	0	Non-Significant

Table 7.19 presents the direct effects that ML has on the following endogenous latent variables: job satisfaction, organizational commitment, and MN. The sizes of the effects on job satisfaction and organizational commitment have a high magnitude, and the one on MN has a low magnitude. They are all significant at the P<0.01 level. This significance shows that ML has

a significant and direct effect on job satisfaction, organizational commitment, and the use of a mix of communication media with higher degrees of naturalness.

Table 7.19: Direct effect of ML

	Total Effect	Effect Size	P Value
ML→SAT	0.742	0.557	<0.001
ML→COM	0.73	0.538	<0.001
ML→MN	0.637	0.135	<0.001

Table 7.20 shows the sum of the indirect effects that ML has on job performance. Since this study does not hypothesize a direct link between ML or MN, the only effect that this endogenous latent variable can have on the former latent variables is an indirect one. This effect is small according to the previously discussed criteria, and its P value is significant at the P<0.001 level. This effect shows that the ML by a supervisor has a small indirect effect on job performance of an employee.

Table 7.20: Sum of indirect effect of ML

	Paths	Indirect Effect	Effect Size	P Value
JP	2	0.293	0.05	<0.001

Table 7.21 shows the total of the indirect effects that MN has on job performance. As the table shows, MN has no effect on job performance in this study.

Table 7.21: Sum of indirect effect of MN

	Paths	Indirect Effect	Effect Size	P Value
JP	2	-0.006	0	Non-Significant

Table 7.22 shows the total effects that all the latent variables in the model have on the endogenous latent variable job performance. The table shows that job satisfaction has one path

pointing to job performance, which has a small effect on the former that is significant at the P<0.01 level. This effect means that job satisfaction has a small but statistically significant effect on job performance. It also shows that organizational commitment has a small but statistically significant effect on job performance. This effect is at the P=0.002 level.

Table 7.22 also shows that ML has two paths pointing to job performance. The table shows that one of these paths in the model is mediated by job satisfaction, and the other one by organizational commitment. Thus, the effect that ML has on job performance is indirect in nature. The table also shows that the size if the effect is small but once again is a statistically significant one. This effect means that the frequency of using ML by a supervisor affects an employee's job performance in a small but measurable manner. The table also shows the indirect effect that MN has on job performance. The size of this effect is below the threshold value for small and is statistically non-significant.

Table 7.22: Total effect of all latent variables on job performance

	Paths	**Total Effects**	**Effect Size**	**P Values**
SAT	1	0.289	0.117	<0.001
COM	1	0.107	0.039	≤0.01
ML	2	0.293	0.089	<0.001
MN	2	-0.006	0	Non-Significant

Multigroup analysis: Differences between the US and India subsamples

In order to analyze possible differences between the US and India subsamples, this study conducts a multigroup analysis. The analysis uses WarpPLS 6.0 by choosing the *explore multigroup analysis* option. The grouping by variable type uses the *unstandardized indicator*, and the grouping by variable option was set to the indicator *Ctry10UI*. The analysis method is *constrained latent growth*. This process segments the data according to the selected variable in order to analyze all possible pairings (Kock, 2017).

Table 7.23 shows the path coefficients of the US and India subsamples. Upon initial analysis, the path coefficients of the two subsamples appear to be mostly similar. Table 7.24 shows that the full collinearity VIFs are below the threshold value of 5 (Hair et al., 2011; Kline, 2005; Kock, 2017) for both subsamples. This value indicates that excessive collinearity from one subsample is not being subsumed by the other subsample's lack of collinearity.

Table 7.23: Path Coefficients

	ML-US	ML-IN	JP-US	JP-IN	JP-IN	ML*MN-US	ML*MN-IN
MN	0.495	0.528					
SAT	0.662	0.744	0.21	0.355		0.05	-0.035
COM	0.663	0.688	0.141	0.14		0.012	-0.049
Gdr			-0.083	-0.008			
Ed			-0.135	0.096			
Tenure			0.052	0.043			
Exp			0.191	0.102			
Mgmt			0.069	0.125			
Income			-0.019	-0.115			

Table 7.24: Full Collinearity VIFs

	ML	MN	Sat	Com	JP	Gdr	Ed	Tenure	Exp	Mgmt	Income	MN*ML
US	2.284	1.578	3.087	3.359	1.161	1.073	1.083	1.334	1.380	1.179	1.067	1.524
IN	2.841	1.426	4.733	4.065	1.406	1.085	1.202	1.789	1.844	1.366	1.057	1.865

Table 7.25: Absolute Differences in Full Collinearity VIFs

ML	MN	Sat	Com	JP	Gdr	Ed	Tenure	Exp	Mgmt	Income	MN*ML
0.558	0.152	1.646	0.706	0.245	0.012	0.119	0.455	0.463	0.187	0.01	0.341

Table 7.26 shows that the absolute latent growth coefficients are quite small. Table 7.27 shows the P-values for the absolute latent growth coefficients on Table 7.26. As mentioned above, the method used for this analysis is constrained latent growth, which treats the segmenting variable or indicator as a moderating variable by estimating the interaction effects between it and all the paths in the model at once without actually including any links in the

model. Therefore, the absolute latent growth coefficients are akin to the moderating effect that the country of origin of the respondent has on the paths in the model.

According to this analysis, the only latent growth coefficients that are statistically significant and relevant is the one corresponding to the ML – MN path, although the resulting difference in the path coefficients of the two subsamples is only of 0.033 (0.528-0.495). The other two absolute latent growth coefficients that are statistically significant are the ones that are related to the moderating effect that MN has on ML. However, these statistically significant absolute latent growth coefficients are not regarded as relevant since they correspond to model paths that have non-significant path coefficients. The above findings seem to indicate that, aside from a small difference in the ML – MN path, there is no statistical significance between the models of the US and India subsamples.

Table 7.26: Absolute Latent Growth Coefficients

	ML	JP	ML*MN
MN	0.149		
SAT	0.042	0.083	0.147
COM	0.027	0.066	0.108
Gdr		0.003	
Ed		0.066	
Tenure		0.065	
Exp		0.07	
Mgmt		0.013	
Income		0.011	

A power analysis was conducted for each of the two subsamples. This was done by using the “View or change data modification settings” from the “Setting” menu option in WarpPLS 6.0. The Indicator *Ctry10UI* was restricted to 1 for the US subsample and to 0 for the India subsample and a power analysis was conducted for each. The analysis indicates that the US model has a power of 0.866 and the India model a power of 0.812, both at the 5% significance level.

Table 7.27: P-values for Absolute Latent Growth Coefficients

	ML	JP	ML*MN
MN	0.002		
SAT	0.209	0.054	0.002
COM	0.302	0.101	0.019
Gdr		0.048	
Ed		0.101	
Tenure		0.107	
Exp		0.091	
Mgmt		0.4	
Income		0.417	

Measurement Invariance: Differences between the US and India subsamples

This study analyzes the differences between the measurement models for the Indian and US subsamples with a measurement invariance analysis. This analysis uses the *explore measurement invariance* option from the *explore* menu option in WarpPLS 6.0.

Table 7.28 shows the factor loadings on the latent variables for the Indian subsample.

Table 7.29 shows factor loadings on the latent variables for the US sample. The two tables clearly show that the loadings are quite similar for both subsamples.

Table 7.30 shows the absolute latent growth coefficients for the factor loadings. The grouping variable type was set to *unstandardized indicator*, and the grouping variable option was set to the indicator *Ctry10UI*. The analysis method is *constrained latent growth*. As above, this process segments the data according to the selected variable to analyze all possible pairs (Kock, 2017). The table shows that the absolute latent growth coefficients are quite small.

Table 7.31 shows the P-values for the absolute latent growth coefficients for Table 7.30. The two tables shows that not only are the coefficients small but are statistically non-significant. These coefficients indicate that there is no statistical difference in how the factors load on the latent variables in the US and India subsamples.

Table 7.28: Loadings for India subsample

	ML	MN	Sat	Com	JP	MN*ML
LD	0.934					
LE	0.955					
LM	0.913					
MD		0.928				
ME		0.946				
MM		0.868				
SAT1			0.908			
SAT2			0.9			
SAT3			0.896			
SAT4			0.901			
SAT5			0.809			
COM1				0.881		
COM2				0.875		
COM3				0.896		
COM4				0.796		
COM5				0.776		
JP1					0.614	
JP2					0.793	
JP3					0.727	
JP4					0.69	
JP5					0.647	
JP6					0.68	
JP7					0.724	
JP8					0.728	
JP9					0.678	
MD*LD						0.952
MD*LE						0.951
MD*LM						0.888
ME*LD						0.927
ME*LE						0.924
ME*LM						0.932
MM*LD						0.907
MM*LE						0.901
MM*LM						0.876

Table 7.29: Loadings for US subsample

	ML	MN	Sat	Com	JP	MN*ML
LD	0.919					
LE	0.892					
LM	0.839					
MD		0.889				
ME		0.906				
MM		0.769				
SAT1			0.935			
SAT2			0.939			
SAT3			0.919			
SAT4			0.946			
SAT5			0.874			
COM1				0.832		
COM2				0.89		
COM3				0.909		
COM4				0.819		
COM5				0.768		
JP1					0.725	

Table 7.29: Loadings for US subsample (Countinued)

	ML	MN	Sat	Com	JP	MN*ML
JP2					0.817	
JP3					0.831	
JP4					0.786	
JP5					0.748	
JP6					0.799	
JP7					0.792	
JP8					0.717	
JP9					0.812	
MD*LD						0.836
MD*LE						0.808
MD*LM						0.8
ME*LD						0.881
ME*LE						0.856
ME*LM						0.858
MM*LD						0.817
MM*LE						0.842
MM*LM						0.746

Table 7.30: Absolute Latent Growth coefficients for loadings

	ML	MN	Sat	Com	JP	MN*ML
LD	0.042					
LE	0.008					
LM	0.037					
MD		0.001				
ME		0.013				
MM		0.014				
SAT1			0.015			
SAT2			0.008			
SAT3			0.011			
SAT4			0.019			
SAT5			0.025			
COM1				0.007		
COM2				0.005		
COM3				0.013		
COM4				0.012		
COM5				0.025		
JP1					0.045	
JP2					0.05	
JP3					0.036	
JP4					0.027	
JP5					0.026	
JP6					0.008	
JP7					0.034	
JP8					0.068	
JP9					0.028	
MD*LD						0.034
MD*LE						0.026
MD*LM						0.059
ME*LD						0.005
ME*LE						0.064
ME*LM						0.038
MM*LD						0.004
MM*LE						0.05
MM*LM						0.022

Table 7.31: P-values for the Absolute Latent Growth coefficients for loadings

	ML	MN	Sat	Com	JP	MN*ML
LD	0.21					
LE	0.438					
LM	0.241					
MD		0.492				
ME		0.403				
MM		0.398				
SAT1			0.384			
SAT2			0.438			
SAT3			0.417			
SAT4			0.359			
SAT5			0.32			
COM1				0.446		
COM2				0.462		
COM3				0.405		
COM4				0.41		
COM5				0.316		
JP1					0.193	
JP2					0.169	
JP3					0.249	
JP4					0.301	
JP5					0.307	
JP6					0.442	
JP7					0.255	
JP8					0.096	
JP9					0.298	
MD*LD						0.256
MD*LE						0.312
MD*LM						0.13
ME*LD						0.463
ME*LE						0.11
ME*LM						0.232
MM*LD						0.472
MM*LE						0.17
MM*LM						0.34

In summary, the above multigroup and measurement invariance analyses support the use of one sample instead of two subsamples for the purpose of this study, since the differences are minimal.

CHAPTER VIII

DISCUSSION

The fields of Organizational Behavior and Leadership have been somewhat receptive to the idea that communication in the organization involves more that the reduction of uncertainty (J. Mayfield & Mayfield, 2018; J. Mayfield et al., 1995; Sullivan, 1988). But receptiveness has arguably not been the case in the computer mediates communication (CMC) research that have traditionally used MRT and other related theories that have inherited the implicit communicational restrictions imposed by the need-deficiencies paradigm (Sullivan, 1988). The way in which people communicate is rapidly changing (Moqbel, 2012), and the array of tools to do so is rapidly growing and evolving (Gerber, 2017; Rauv, 2017). This study adds to the body of knowledge that examines the roles that electronic communications have in the workplace by proposing a CMC measurement scale that is not shackled by the implicit limitations of the need-deficiencies paradigm: the media naturalness scale (MNS), and the related construct of the communication stream. This study also adds to the growing body of empirical evidence in support of the motivating language theory (MLT) (J. Mayfield & Mayfield, 2018).

Overview of the Findings

The purpose of this study is to develop a MNS and use it in the context of an empirical study. The study finds support for the MNS in the adequate measures of the convergent and discriminant validities for the scale in both the pilot and the main studies. A second area of support for the MNS comes from the full analysis of the latent growth coefficients that compares the factor loadings between the India and US subsamples in the main study. These results show that the MNS is cross-culturally valid because there are no measurable differences between the factor loadings of the India and US subsamples. The largest full latent growth coefficient reported has a value of 0.068 with P=0.096, which was for the eighth indicator of the PERF (job performance) variable. This P value was also the smallest in the comparison. A third area of support for the validity of the MNS is the internal similarities between the models of the pilot study and the main study, some of which are shown on Table 8.1. One of the most salient similarities between the pilot and main study is in their first-order models. The first-order latent variable that represents the degree of naturalness of the meaning-making language (MML) has the lowest composite reliability score, average variance extracted, and full collinearity variance inflation factor in both studies. Another similarity between the pilot and main studies is in their second-order models. They show that the endogenous latent variable job performance (Perf) has the lowest average variance extracted and full collinearity variance inflation factor in both studies.

Table 8.1: A few similarities between the pilot study and the main study

	Pilot- First-order	Main- First-order	Pilot- Second-order	Main- Second-order
Min. Loading	0.661	0.59	0.628	0.64
Max. Loading	0.916	0.882	0.945	0.915
Highest Loading P value	P<0.001	P<0.001	P<0.05	P<0.001
No. Indicators removed	0	0	0	0
Lowest CR score	0.922 (MM)	0.888 (MM)	0.869 (Perf)	0.873 (MN)
Lowest Cronbach's alpha	0.901	0.88	0.854	0.873
Lowest AVE	0.63 (MM)	.502 (MM)	0.441 (Perf)	.511 (Perf)
High FC-VIF	4.582 (LD)	4.384 (ME)	3.126 (Com)	4.695 (Sat)
Low FC-VIF	2.948 (MM)	2.024 (MM)	1.273 (Perf)	1.279 (Perf)
Average Path Coefficient			0.247 P=0.004	0.210 P<0.001
Average R^2			0.223 P=0.004	0.371 P<0.001
Average VIF			1.222	1.594

Notes: **MM**=First-order LV that measures MN for ML's Meaning Making Dimension; **ME**= First-order LV that measures MN for ML's empathetic language dimension; **LD**=First-order LV representing ML's direction giving language dimension.

The strategy of this study is to include variables and relationships in the research model that studies have previously used and supported in the context of ML. In this manner, this study is supported by obtaining confirmatory findings that are consistent with the literature (J. Mayfield & Mayfield, 2018; Porter et al., 1974; Riketta, 2002; Zhang & Zheng, 2009). Thus, this study examines the moderating effect of MN on the previously studied relations between ML and job satisfaction, as well as ML and organizational commitment. The fact that the findings of the moderating effect of MN on ML are not consistent across the pilot and main studies are evidence of a lack of support. After all, support for the moderating effect of MN on ML was only found in the smaller pilot study. From this perspective, the MNS gains additional support because it behaves similarly in both studies.

These findings also show conflicting support from two different studies, with distinct samples. The issue of whether a sample is representative of a population or not is a recurring one, and especially so when using convenience samples. This is true whether these samples come from surveys in person or around a university campus, distributed online, or by using some form of crowdsourcing like MTurk (Kittur et al., 2008). While Turkers are more diverse than most convenience samples (Berinsky et al., 2011; Kittur et al., 2008), they are not necessarily representative of their respective populations in ways that are similar to the differences between internet users and non-internet users (Paolacci & Chandler, 2014). If this is indeed the case, then not being representative could explain why the moderating effect of MN on ML in the main study is both insignificant and statistically non-significant even though supervisors have an inclination to use communication channels with a higher degree of naturalness in both studies (as evidenced by the significant ML→MN path coefficient) when using ML. A possible reason why this moderating effect is not found could be that the schema alignment proposed by Kock is not implemented in the current study. In this case, a high degree of experience with various forms of CMC allows a higher perception of naturalness (Kock, 2004). If this is indeed the correct explanation for these findings, one could conceivably expect to find that if schema alignment is adequately measured, the moderating effect of MN on ML would increasingly become statistically significant in a manner that is consistent with the pilot study. This perspective also provides additional support to the MNS by showing that it behaves in a similar fashion when used with different subsamples.

The proposed research model had a good fit with the data collected for both the pilot and the main study, as shown in the corresponding chapters. The path coefficients of both studies and their corresponding P values are listed on Table 8.2. The variance explained (R^2) of the dependent variables are listed in Table 8.3.

Table 8.2: Comparison of findings in the Pilot and Main Studies

Path	**Pilot Study**	**Main Study**	**Research Purpose**	**Type of Support**	**Support Found**
ML→SAT	β=0.59-Y P<0.01	β=0.74-Y P<0.01	Confirmatory	Previous, Empirical	Confirmatory
ML→COM	β=0.61-Y P<0.01	β=0.73-Y P<0.01	Confirmatory	Previous, Empirical	Confirmatory
ML→MN	β=0.43-Y P<0.01	β=0.37-Y P<0.01	Exploratory	Proposed	Empirical
MN*ML→SAT	β=0.20-Y P=0.02	β=0.02-N **P=0.38**	Exploratory	Proposed	Contradictory
MN*ML→COM	β=0.23-Y P<0.01	β=0.02-N **P=0.38**	Exploratory	Proposed	Contradictory
SAT→PERF	β=0.24-Y P<0.01	β=0.29-Y P<0.01	Confirmatory	Previous, Empirical	Confirmatory
COM→PERF	β=0.19-Y P=0.02	β=0.11-Y P=0.02	Confirmatory	Previous, Hypothetical	Confirmatory

Table 8.3: Variance of Dependent Variables for each Study

Dependent Variable	Pilot Study	Main Study
MN	R^2=0.19	R^2=0.13
SAT	R^2=0.31	R^2=0.56
COM	R^2=0.33	R^2=0.54
PERF	R^2=0.21	R^2=0.24

The convergence of these confirmatory findings with the literature provides support not only for this study, but also adds to the growing body of support for these findings in the ML literature (J. Mayfield & Mayfield, 2018). The path ML→SAT has a coefficient of β=0.59 in the pilot study and one of β=0.74 in the main study. In both studies the coefficients are statistically significant at the 1% level. These levels are close to the higher bimodal value of β=0.65 reported by Mayfield and Mayfield (J. Mayfield & Mayfield, 2018). The path ML→COM has a coefficient of β=0.61 in the pilot study and one of β=0.74 in the main study. In both studies the coefficients are statistically significant at the 1% level. The β=0.57 reported by Mayfield and Mayfield (J. Mayfield & Mayfield, 2018) is close to the level reported in the pilot study, but lower than the reported value in the main study. Nonetheless, the direction of the path coefficient is supported.

From a theoretical perspective, this study also contributes to the job satisfaction, organizational commitment, and job performance literature from the perspective of ML by further confirming the findings of other studies. The path COM→PERF has been hypothesized in literature, but no definite empirical support has been found (J. Mayfield & Mayfield, 2018; Porter et al., 1974; Riketta, 2002; Zhang & Zheng, 2009). This path is supported by this study; although the pilot study finds a coefficient of β=0.19 and the main study one of β=0.11, the significance level in both cases is 2%. The SAT→PERF path has been supported in the past. Judge et al. reports that the average path coefficient is β=0.30 (Judge et al., 2001). The path coefficient in the pilot study is β=0.24 and in the main study it is β=0.29, with both being statistically significant at the 1% level. Finally, Mayfield and Mayfield report that: “The relationship between ML and follower performance has been largely stable across different situations and measurements with a median r of 0.17” (J. Mayfield & Mayfield, 2018, p. 79), Regarding this variable, the pilot study has an explained variance (R^2) of 0.21 and in the main study one of R^2=0.24; both values are close to those previously reported. Table 8.4 lists the support found in the form of path coefficients and variance that is explained in the literature.

Table 8.4: Summary of previous support for dependent variables

Variable(s)	Previous Support	Citation	Value	Pilot Study	Main Study
ML-COM	Correlation	(J. Mayfield & Mayfield, 2018)	0.24 - 0.57	β=0.61-Y	β=0.61-Y
ML-SAT	Correlation	(J. Mayfield & Mayfield, 2018)	0.35 OR 0.65	β=0.59-Y	β=0.74-Y
COM-PERF	Hypothetical	(Porter et al., 1974) (J. Mayfield & Mayfield, 2018) (Riketta, 2002) (Zhang & Zheng, 2009)		β=0.19-Y	β=0.11-Y
SAT-PERF	Correlation	(Judge et al., 2001)	0.30 (AVG)	β=0.24-Y	β=0.29-Y
PERF	Variance	(J. Mayfield & Mayfield, 2018)	Median R^2=0.17	R^2=0.21	R^2=0.24

Strengths of the Study

Overall, the results of the study indicate that the validities of both the pilot study and the main study are supported through their confirmatory findings, as is evidenced by the direction and magnitude of the related path coefficients and the R^2 of the endogenous variables. The key strength of the study is not only that it demonstrates the MNS in both the pilot and main studies, but that the measurement validity of the instrument is supported in both studies. Additionally, the robustness of the MNS was demonstrated in a cross-cultural setting, and arguably across different subsamples. A second strength comes directly from the nature of MNT itself in that it is not based on the need-deficiencies paradigm (Kock, 2004), and thus is especially suited as a theoretical lens from which to examine forms of communication that are implicitly excluded by other CMC theories.

A third strength of the study is the introduction and use of the communication stream. This gives the researcher the added flexibility to examine communications in a very similar manner to what occurs in everyday life. That is, this study aggregates a series of communications across different channels that have one theme in common with each indicator of ML. The use of the communication stream is the fourth strength of this study; this study examines various CMC at once without the need for pairwise comparisons.

As has been touched upon previously, a key strength of the study is closely related to one of the strategies in the study, the use of a pilot study and a main study. This strategy has served to strengthen the validity of the MNS with the exploratory and explanatory relationships and variables.

Another strength of the study is the use of not only previously documented relationships between variables but of well documented variables and their explained variance. When similar values are encountered in both the pilot and main studies, it further reinforces the validity of the findings as well as of the measurement validity of the scale.

An additional strength of the study is the use of samples from two different countries in the main study. This strength is additionally enhanced by conducting a full latent growth analysis to demonstrate that there were no statistical differences in how the samples behaved that gave the study additional statistical power.

This last strength of the study (which may be arguable) is that different subsamples have been used, as has been discussed previously. The actual nature of the subsamples depends on whether, as some scholars argue, the comparison of traditional random sampling versus convenience samples that are obtained from MTurk indeed have similar differences to those found between traditional random sampling and random samples of internet users (Paolacci & Chandler, 2014), or whether it is simply a case of MTurk samples being more diverse as other scholars have argued (Berinsky et al., 2011; Kittur et al., 2008). In either case, if it is the case that the main study's sample differs from the actual population, then the study has proven itself robust to the use of subsamples. This is true for the confirmatory relationships and variables that lends additional support to the research streams that highlight the importance of ML in affecting organizational outcomes such as job satisfaction, job performance, and organizational commitment. It is also true for the validity of the MNS: The scale is valid in a traditional sample, internet sample, domestic sample, foreign sample, as well as with either significant or non-significant results.

CHAPTER IX

CONCLUSION

Overview

The focus of the study is the development of the MNS and its implementation in an empirical study. The study examines the moderating effect that MN has on the ML→SAT and ML→OC relationships, and how these ultimately affect job performance. As a whole, the findings are consistent among the main and pilot studies regarding the MNS. The findings are also consistent among the US and India subsamples of the study. As evidenced by the cultural manipulation checks, the samples are culturally distinct from one another, and a full latent growth analysis shows that there is no statistical difference on how these subsamples behave regarding the ML scale or the MNS. This similarity allows the subsamples to be used as one and lends additional statistical power to the main study.

The validity of the MNS is supported in both the pilot and the main studies. The confirmatory hypotheses are supported and their related path coefficients as well as variance explained are consistent with the literature. Thus not only is the validity of the MNS reiterated, but that of the study as a whole. Contrary to expectations, the MN does not have a moderating effect on ML in the main study, which is a finding that appeared promising in the pilot study. This apparent contradictory finding may have different implications not only in the field of ML, but in other fields of management and organizational behavior.

The findings show that supervisors use forms of communication that are more natural when engaging in ML. They also indicate that it may not matter how natural the form of communication is as long as ML is being used. Alternatively, it may mean that Turkers have a schema alignment that significantly differs from the normal population as far as MN is concerned. The study also finds that the MNS has similar validity in the US and in India. This same cross-cultural validity is also true for ML, organizational commitment, job satisfaction, and job performance. These results could mean that further study is needed regarding the nature of the moderating role of MN on ML, or to determine if such a moderating effect exists under certain conditions that may require increased use of ML.

This study is the first to propose and validate an instrument to measure MN. It is also the first study to attempt to examine how various forms of electronic communications moderate the effect that ML has on various organizational outcomes (J. Mayfield & Mayfield, 2018; Wang, Fan, Hsieh, & Menefee, 2009). It is also arguably the first quantitative measurement of CMC that is free of the implicit communicational restrictions of the need-deficiencies paradigm (Sullivan, 1988).

Limitations

No study is free of limitations, and this study is no exception. One such limitation is the use of self-reported measures. For example, the overreporting of organizational commitment in this study's survey could reflect the employees need to fit in and be accepted rather than an emotional attachment to their job. Therefore, the study is susceptible to social desirability response bias (Ganster, Hennessey, & Luthans, 1983). Relatedly, self-reported measures of performance have well documented criticism, where perhaps the most notorious line of research has been the one initiated by Dunning and Kruger's colorful and descriptive work titled *Unskilled and Unaware of It: How Difficulties in Recognizing One's Own Incompetence Lead to Inflated Self-Assessments* (Kruger & Dunning, 1999). Although it initially encompassed the social and cognitive domains of performance, additional research has highlighted the difference between the self-evaluation of task performance and actual task proficiency. The finding that many studies have consistently duplicated is that low performers have a tendency to overestimate their performance, while top performers have a tendency to underestimate it (Burson, Larrick, & Klayman, 2006; Ehrlinger & Dunning, 2003). Lastly, the measurement of ML and MN may be susceptible to inaccurate recall of the events in question that leads to recall bias (Mann, 2003).

Another kind of limitation, or possible complication is related to the wording of the ML scale. Each Likert item on the scale ranges from “Very Little” on the minimum side of the spectrum to “A whole lot” on the maximum side of the spectrum. In order to maintain consistency in the wording, the corresponding items that were intended to measure the naturalness of the communication stream of each Likert item were worded similarly. A possible complication that may arise if a respondent wishes to communicate that no such communication has happened. In which case they are forced to choose “Very Little” for ML, or could ostensibly choose random MN values, or select all of the CMC channels and choose a minimum value. Unfortunately, being an exploratory study, this shortcoming did not become evident until after the data was collected, the analysis was concluded, and the findings were reported. This shortcoming could possibly be remedied by arithmetic mean imputation where certain values are detected in both the ML scale, as well as the naturalness of the communication stream.

Another possible shortcoming stems from the use of nonprobability samples in both the pilot and the main studies. Additionally, the pilot study has a smaller sample and thus lacks the generalizability that the main study has. Although the interviews were conducted in person by students that were personally trained by the researcher, the generalizability of the findings is still a potential issue. Especially since the city that they were conducted in (Laredo, Texas) is on the border with Mexico, and therefore can be considered as more culturally similar to Mexico than the United States. As Arreola says in his forthcoming book, not only is the borderland with

Mexico distinct from the US, but “Mexican South Texas regionally and culturally is a distinctive part of the Hispanic American borderland” (Arreola, 2019) (Paragraph 16).

Although there is a body of evidence that supports the quality of the data from convenience samples that use MTurk (Berinsky et al., 2014; Buhrmester et al., 2011; Chandler & Shapiro, 2016; Clifford et al., 2015; Peer et al., 2014; Shapiro et al., 2013), the fact remains that it is still a convenience sample and as thus may not be representative of the population at large. While the use of a convenience sample may not be a problem in and of itself, in the *Annual Review of Clinical Psychology* Chandler and Shapiro report the following about Turkers: “Numerous findings suggest that workers are above average in cognitive aptitude: They score higher than the general population on measure in a range of areas including (…) computer literacy” (Chandler & Shapiro, 2016, p. 58). As mentioned previously, not being representative could indeed explain why the expected moderating effect of MN on ML was found in the main study.

Another possible limitation that is related to the use of a sample from India in MTurk is that although Indian Turkers are highly educated, they consistently produce lower quality data, and that instructional manipulation checks and reverse coded data are especially problematic. This low quality data have led other authors to suggest that language difficulties may be an issue (Chandler & Shapiro, 2016). Although this study does not contain instructional manipulation checks or reverse coded items, the rejection rate for the Indian subsample (34%) was greater than that of the US subsample (21.6%), which coincides with these findings. This possible limitation may have been overcome by the rejection of observations based on the “heart attack” question in the study. Although the cultural manipulation check shows that the two samples are culturally distinct, the results from the full latent growth coefficients analysis, which shows that there is no statistical difference in the loadings of the first- and second-order models when comparing the

US and India subsamples, could arguably be the product of a non-representative sample.

The development of the MNS as it is presented in this study also has its limitations. The most obvious of these is the fact that it does not address the MNT's schema alignment proposition, although a compelling argument has been made as to why this would not affect this study: from the perspective of the MNT, this is where culture would fit. To remedy this limitation, a series of qualitative ethnographic studies could be conducted to determine some sort of schema alignment between cultures.

Another limitation arises from the fact that the self-reported measures do not account for cognitive adaptation, since the burden of adaptation falls on the encoder (Kock, 2007). Thus, the cognitive adaptation proposition is only partially addressed in the MNS in the form of an allowance for compensatory adaptation. By allowing three points for compensatory adaptation, the implication is that the score becomes a measure of the medium's capability to support low, medium, or high compensatory adaptation, which is arguably limited. Additionally, this allowance for the possibility of compensatory adaptation is exactly that: an allowance for a behavior that may take place, not a measure of the actual behavior.

Another possible limitation of the proposed MNS is derived from the fact that, as discussed previously, the points that are assigned to the different aspects of the human communication apparatus are derived from a reverse ranking of the features. This ranking poses challenges similar to those faced by a reverse coded Likert-type scale, where the score obtained is arguably not a summation of the interval but rather of ordinal values. The research argues that this approach implicitly converts ordinal data to interval data and thus assumes equidistance between points, which can be problematic as well as controversial (Jamieson, 2004). For example, the difference in the points assigned between spoken language (4 points), and facial expression (3 points) could be misinterpreted to mean that spoken language is 33% more important than facial expression.

Another possible limitation is that the degree of naturalness of the communication stream will inherently suffer from the limitations of the MNS. The use of reverse rankings in the MNS and Likert items in measuring the frequency of use of various CMC could arguably be problematic. After all, an assumed conversion from ordinal to interval data (in the MNS) could be used to compose another measure (naturalness of the communication stream) that again, inherently converts ordinal data to interval data. However, the possible alternatives are also problematic and are discussed below.

Last of all, at least regarding the MNS, is that additional forms of CMC are possible other than those proposed in this study. Examples of these would be knowledge bases, wikis, and instructional videos as well as collaboration platforms such as Microsoft Teams or Slack. A particularly challenging one could be Slack because it is basically messaging but can be extended with many different third-party services.

Further Study

The first and most obvious area of further study is that of the possible improvement of MNS. First of all, in order to increase the robustness of the scale, there would ideally be studies that confirm the rankings of the elements of the human communication apparatus that have been proposed in this study. Some suggestions in this respect could include rephrasing the hypothetical scenario so the phrasing is about communication rather than communication in the workplace. Other questions that may warrant further research are for example related to whether the speech imperative proposition does not hold in certain cases. The imposition of the speech imperative proposition was interpreted by some as a restriction, so could ranking change with changes to situations in the hypothetical scenarios?

Additionally, further experimental research may yield additional insights into a better system of weight for features of the human communication apparatus and may find possible unforeseen effects. For example, the possible existence of synergies could explain why the inclusion of certain concurrent elements may provide additional benefits. Such may be the case for face-to-face communication: its naturalness alone cannot be explained by the elements themselves, but rather the inclusion of all the elements (it may be synergistic in nature). In other words, the impact of face-to-face meetings may have an inordinate impact on the perceived naturalness of a communication stream that leads to a quasi-asymptotic relation. As mentioned above, it is quite feasible that speech is more than 33% more important than the conveyance of facial expressions, as is implied by the system of points proposed in this study.

As mentioned previously in this section, compensatory adaptation has only been partially addressed. A more comprehensive approach than the simple inclusion of three points for compensatory adaptation could be an identification of proxies for elements of naturalness, such as emojis, emoticons, feelings (as in Facebook interactions), GIFs, <<sarcasm font>> etc., which can serve as proxies for body language and facial expressions. Another example is exaggerated body language, which is a form of compensatory behavior in videos. Additional study may be needed in determining the actual mechanisms or behavior of compensatory adaptation. In the above case, just because points are added to a CMC simply because of its ability to support compensatory adaptation, it does not mean that compensatory adaptation is used.

A further study of the applicability of the schema alignment proposition in different scenarios may also be in order. For example, technological proficiency as a schema. A different level of schema on technological proficiency may explain the lack of a moderating effect of MN on ML. This conjecture would be consistent with the differences among the samples that were mentioned above. If this is indeed the correct explanation for these findings, one could conceivably expect to find that if schema alignment is adequately measured, the moderating effect of MN on ML would increase and become statistically significant in a manner similar to the pilot study.

Another possible implementation of the above schema alignment perspective is the study of situations of organizational change or uncertainty seen as changes in organization schema: One of the reasons that Kotter lists for the failure of transformation efforts is "Undercommunicating the Vision by a Factor of Ten" as "Without *credible* communication, and lots of it, the hearts and minds of the troops are not captured." (italics added for emphasis were not in the original article) (Kotter, 1998, p. 63). From the perspective of MNT, it is possible that in times of change, such as the ones mentioned by Kotter, the mental schemas of the leadership of the organization and "the troops" become misaligned. If this is indeed the case, then not only is more communication needed, but also communication that has a higher degree of naturalness may be necessary. An interesting line of study in this area could be the exploration of the role that meaning-making language may play in the process of schema re-alignment, what the effect of MN is in MML, and how this may affect the outcome of the specific organizational situation underlying the initial schema misalignment.

While improvements in the MNS, such as the specification of weights mentioned above, will translate to the naturalness of the communication stream, there may arguably be room for improvement at the communication stream level. One possible alternative to the use of Likert-type items in measuring the frequency of use of CMC could be the implementation of a constant-sum scale. Although this approach has the possibility of solving the ordinal to interval implicit conversion issue as well as (arguably) being more accurate, it brings its own set of shortcomings and challenges. First of all, constant-sum scales are more mentally demanding, and therefore work best with respondents that have a higher level of education (Zikmund, 2003). Additionally, there is the possibility of including recall bias (Mann, 2003), which may negate the perceived increase in accuracy. Another area of possible study is the unit of communication that is being measured. For this study what was measured was the perceived frequency of use of a CMC. The possible issue is that the time spent using a medium can be misleading due to different levels of fluency in different CMCs. Another possibility is to attempt to measure the actual communication through phrasing similar to: "How much of your supervisor's communication…". This could be achieved through a Likert-style item or a constant-sum item, both of which have limitations and complications that have been discussed.

While the MNS as presented in this study has a lot of room for improvement, it may also hold great promise. Because of its foundations on Darwinian evolution and evolutionary psychology (Kock, 2004), MNT is not a rational choice model for CMC and thus needs not be constrained to the more traditional deterministic form of research that has drawn so much criticism from social theorists and offers an alternative to researchers that study CMC from a more holistic perspective than that of uncertainty reduction.

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Appendix A: Clarifications to Committee Member Questions

Control Variables: Literature and Rationale

Gender

While it has been established that cognitive functions differ slightly between men and women (Weiss, Kemmler, Deisenhammer, Fleischhacker, & Delazer, 2003), the uncovered differences and related effect sizes are so small as to be considered practically insignificant. Regardless of this, sex roles do affect perceptions (Robbins & Judge, 2013). Heilman and Okimoto (2008) report in their experimental research that not only do married females receive lower scores in *anticipated* job commitment, achievement striving, and dependability than married males, but married females with children received lower scores than those that reported not having children. It is therefore not surprising that research should indicate that women's work experiences should differ from those of males, or that it should be hypothesized that females are treated differently than males by their mentors (Ng & Feldman, 2009). While in their meta-analysis of education and job performance Ng and Feldman (2009) find that gender significantly moderates the effect of education on job performance, the authors hypothesize it may be due to suffering from unequal treatment (selection bias, higher performance standards) or to having more pronounced struggles with work-family balance. Finally, females have also been shown to underreport superior performance on self-evaluations when compared to their male counterparts (Weiss et al., 2003).

Education

In their meta-analysis of 293 studies and 332 independent samples Ng and Feldman (2009) find that education positively influences core task performance, as well as other measures of job performance such as citizenship and conscientiousness. Significant moderators for this relationship were gender, race, job level, and job complexity. The authors explain that education is correlated with intelligence, which in turn facilitates the acquisition of job-relevant knowledge.

Tenure

Ng and Feldman (2009) also study job tenure as a measure of work experience. The authors argue that this experience is likely to provide job-specific tacit knowledge that is not obtained in formal education.

Experience

It is worth noting that in the present study, a distinction is made between work experience and tenure: Work experience is operationalized as the total years that the respondent of the study has been active in the workforce. Similar to the rationale expressed by Ng and Feldman (2009), this study argues that tacit knowledge is gained with experience. The main difference with tenure is that, aside from job-specific knowledge, this variable intends to capture the acquisition of transferrable tacit knowledge.

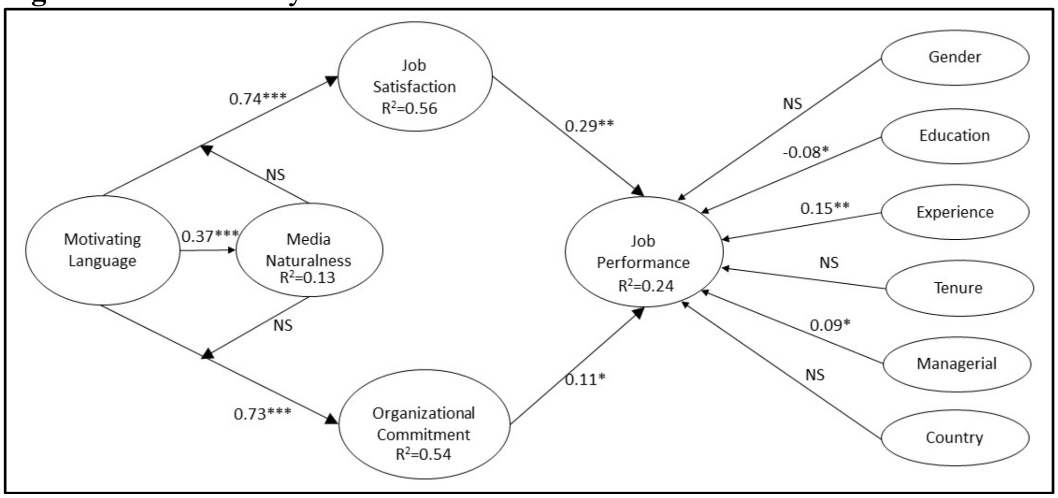
Managerial Rank

Job satisfaction has been found to have a tendency to increase over time among those employees in a managerial position (Robbins & Judge, 2013), which can lead to better job performance.

Comparison of the main study with the control variables originally included in the pilot study

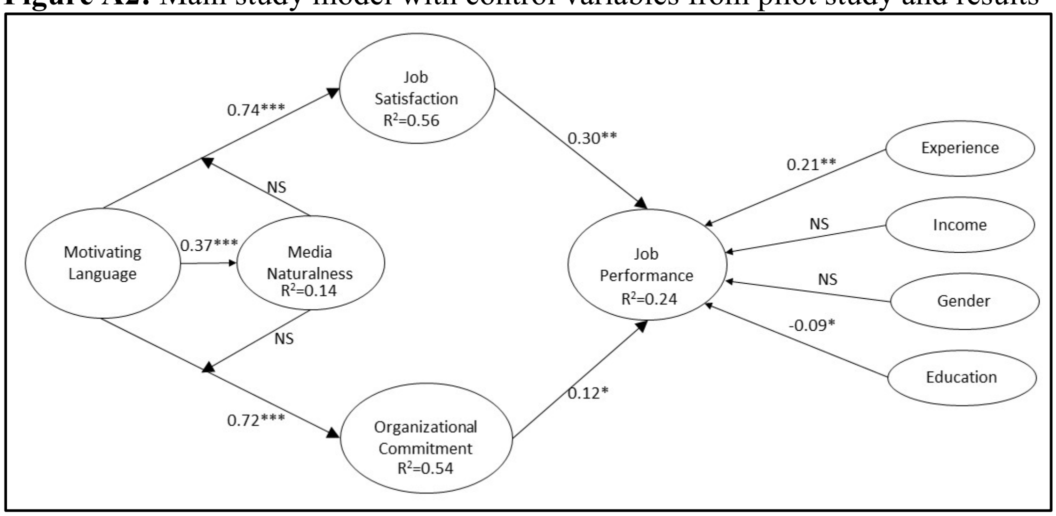
An analysis is made that includes the same four control variables as the pilot study, and it is compared the results of the main study. The model and results of the main study reported in Chpater 7 are now presented in figure A1. The comparison with the four original control variables is presented in figure A2. As is evidenced in the figures, the cchnages in the explained variance of the variables of interest as well as their path coefficients is minimal

Figure A1: Main study model and results



(*) P-Value ≤ 0.05; (**) P-Value ≤ 0.01; (***) P-Value < 0.001; Paths with no coefficients are labeled NS

Figure A2: Main study model with control variables from pilot study and results



(*) P-Value ≤ 0.05; (**) P-Value ≤ 0.01; (***) P-Value < 0.001; Paths with no coefficients are labeled NS

Possible Response Range Restriction in the Pilot Study

A possible explanation for the significant moderating effect of MN on ML in the pilot study is the possibility of range restriction. This possibility is illustrated by the fact that one third of the respondents indicated that they communicate with their bosses exclusively face-to-face, especially in the food service industry. When this high incidence of face-to-face communication is viewed in the light of the CyberStates 2018 report that lists the city of Laredo in the number 2 lowest ranking for STEM jobs (only 13.6 per 1,000) (Berheim, 2019), a clearer picture of lower technology use by the city's population starts to emerge that can explain the range restriction. As was noted in the discussion section of this study, the city of Laredo, Texas is most likely not representative of the United States.

Comparison of the Pilot and Main Studies Path Coefficients

Table A1: Multi-group analysis of path coefficients in the pilot and main studies using the Satterthwaite method, 2-tailed comparison at 5% significance level.

Path	Pilot β	Pilot SE	Main β	Main SE	Multigroup T-Val	Multigroup P-Val (2-Tailed)	Difference
ML→SAT	0.59	0.085	0.74	0.047	-1.5443	0.1232	No
ML→COM	0.61	0.084	0.73	0.047	-1.2467	0.2131	No
MN*ML→SAT	0.20	0.093	-0.02	0.053	2.0553	0.0404	Yes
MN*ML→COM	0.23	0.091	-0.02	0.053	2.3740	0.0180	Yes
ML→MN	0.43	0.086	0.37	0.050	0.6031	0.5467	No
SAT→PERF	0.24	0.092	0.29	0.050	-0.4775	0.6332	No
COM→PERF	0.19	0.092	0.11	0.052	0.7570	0.4494	No

The path coefficients of the pilot and main studies are compared through the use of the Satterthwaite method described by Kock (2014). This method uses the path coefficients, their standard errors and sample sizes to calculate the p-value of a multi-group effect. In order to use a conservative approach, the author of this paper chooses a $p \leq 0.05$ (two-tailed) for the multi-group difference effect. This indicates an overlap of the 95% confidence intervals of the corresponding path coefficients in the pilot and main studies.

Support for Confirmatory Hypotheses

In order to make the results of the study more comparable to previous studies, the analysis for the main study was re-done with older methodology. The outer model algorithm was changed from 'Factor-based PLS Type CFM1' to 'PLS Regression', the default inner model analysis algorithm was changed from 'Warp3' to 'linear', and the resampling method was change from 'Stable3' to 'Bootstrapping'. The key results are reported in table A2. While all the items below were also supported as was previously shown in table 8.4, these results are presented as a measure of robustness.

As can be seen in the table, the values previously reported in the literature for the ML-SAT pair of variables and the R^2 for job performance are reproduced, while the ML-COM and SAT-PERF correlations are very close to the expected values. The relationship among the COM-PERF variables has been widely discussed and hypothesized (Mayfield & Mayfield, 2018; Porter, Steers, Mowday, & Boulian, 1974), but limited evidence has been found (Zhang & Zheng, 2009). The fact that this relationship is demonstrated in this study lends additional support for the PLS-SEM algorithms proposed by Kock (2017).

Table A2: Summary of confirmatory support for dependent variables

Variable or Pair	Previous Support	Citation	Value	Main Study Findings
ML - COM	Correlation	(Mayfield & Mayfield, 2018)	0.24 - 0.57	Confirmed Correlation=0.657
ML - SAT	Correlation	(Mayfield & Mayfield, 2018)	0.35 OR 0.65	Confirmed Correlation=0.667
COM - PERF	Hypothetical	(Porter et al., 1974) (Mayfield & Mayfield, 2018) (Riketta, 2002) (Zhang & Zheng, 2009)		Confirmed* Correlation=0.28
SAT - PERF	Correlation	(Judge, Thoresen, Bono, & Patton, 2001)	0.30 (AVG)	Confirmed Correlation=0.302
PERF	Variance Explained	(Mayfield & Mayfield, 2018)	Median R^2=0.17	Confirmed R^2=0.17

(*) This value is reported with the original settings of 'Factor-based PLS Type CFM1', 'Warp3' and 'Stable3'

Media Naturalness: Correlates to Motivating Language, but Does Not Moderate It

Mayfield & Mayfield mention that motivating language was conceptualized as using "mindful and strategic leader speech" (Mayfield & Mayfield, 2018, p. 8). It therefore not unreasonable to argue that this application of mindfulness and strategy on the leader's part is manifested as improved compensatory adaptation of the message to the communication medium of choice in a manner consistent with Media Naturalness Theory (Kock, 2004). Although Kock (2007) has shown that the burden of compensatory adaptation falls on the encoder, the unit of analysis in this paper is the employee. Because the respondents are the receivers of the motivating language message, the compensatory adaptation behavior is not measured.

Practical Applications

The findings in this paper can lead to important organizational applications. The first of these applications can be related to the motivation of virtual workers or distributed teams. While it appears that motivating language is not affected by the mix us CMC media used to communicate it, this may warrant further inspection. As mentioned above, it may very well be that some of the leaders that use more motivating language are also more mindful about their use of CMC. If this is indeed the case, the possibility exists of conducting *e-leadership* training seminars for those that coordinate virtual workers or distributed teams. These training sessions would likely emphasize the proper use of compensatory adaptation behavior focused on the effective conveyance of motivating language. The principles taught in these sessions will likely be the result of qualitative research in the area of compensatory adaptation behavior in the area of motivating language in order to uncover related best practices.

A second possible application is related to the concept of the communication stream and also somewhat related to the above-mentioned application. It is possible that leaders can be trained in improved media mix use, in order to achieve a communication stream with a more desirable level of naturalness.

A third possible application of the findings and conclusions of this paper is to help clarify the role of CMC in times of organizational change or uncertainty. As mentioned in the discussion section of this paper, the MNT's concept of schema alignment can be applied to organizational culture. Therefore, in times of organizational change, especially when there is a cultural shift, such as in the case of reorganizations, or mergers and acquisitions, adequate naturalness of a communication stream may prove to be quite relevant. In the case of organizational transformation, not only is a lot of communication needed, but it must also be credible (Kotter, 1998), and it is not unreasonable to surmise that a more natural communication stream could make a difference. Particularly because these situations may require the re-emphasizing of the meaning-making dimension of motivating language, which is by nature more personal and informal.

Appendix B: Measurement Instrument

The questions below were answered on a Likert-type with the following options: A Whole Lot (WL), A Lot (A), Some (S), Little (L), Very Little (VL)

Motivating Language (ML)*
The examples below show different ways that your boss might talk to you. Please choose the answer that best matches your perceptions. Be sure to mark only one answer for each question.

- ML-DG-01: Gives me useful explanations of what needs to be done in my work.
- ML-DG-02: Offers me helpful directions on how to do my job.
- ML-DG-03: Provides me with easily understandable instructions about my work.
- ML-DG-04: Offers me helpful advice on how to improve my work.
- ML-DG-05: Gives me good definitions of what I must do in order to receive rewards.
- ML-DG-06: Gives me clear instructions about solving job-related problems.
- ML-DG-07: Offers me specific information on how I am evaluated.
- ML-DG-08: Provides me with helpful information about forthcoming changes affecting my work.
- ML-DG-09: Provides me with helpful information about past changes affecting my work.
- ML-DG-10: Shares news with me about organizational achievements and financial status.
- ML-EL-01: Gives me praise for my good work
- ML-EL-02: Shows me encouragement for my work efforts
- ML-EL-03: Shows concern about my job satisfaction
- ML-EL-04: Expresses his/her support for my professional development
- ML-EL-05: Asks me about my professional well-being
- ML-EL-06: Shows trust in me
- ML-MM-01: Tells me stories about key events in the organization's past
- ML-MM-02: Gives me useful information that I couldn't get through official channels
- ML-MM-03: Tells me stories about people who are admired in my organization
- ML-MM-04: Tells me stories about people who have worked hard in this organization
- ML-MM-05: Offers me advice about how to behave at the organization's social gatherings
- ML-MM-06: Offers me advice about how to "fit in" with other members
- ML-MM-07: Tells me stories about people who have been rewarded by this organization
- ML-MM-08: Tells me stories about people who have left this organization

*The scale is used under a Creative Commons Share-Alike by Attribution license according to the requirements specified by the authors (J. Mayfield & Mayfield, 2008)

Media Naturalness (MN)

Table B1: Presentation of the Media Naturalness measurement items

Please indicate how your boss communicates with you							
1=Very Little, 2=Little, 3=Some, 4=A lot, 5=A Whole Lot		Face-to-Face communication	phone calls	e-mail	Written instructions (handbooks, instruction manuals, etc.)	text messages	Social Media (facebook, twitter, etc)
ML-DG-01	When my boss gives me useful explanations of what needs to be done in my work, he/she uses:						

The following items were used to measure media naturalness in the above format:

- ML-DG-01: When my boss gives me useful explanations of what needs to be done in my work, he/she uses:
- ML-DG-02: When my boss offers me helpful directions on how to do my job, he/she uses:
- ML-DG-03: When my boss provides me with easily understandable instructions about my work, he/she uses:
- ML-DG-04: When my boss offers me helpful advice on how to improve my work, he/she uses:
- ML-DG-05: When my boss gives me good definitions of what I must do in order to receive rewards, he/she uses:
- ML-DG-06: When my boss gives me clear instructions about solving job-related problems, he/she uses:
- ML-DG-07: When my boss offers me specific information on how I am evaluated, he/she uses:
- ML-DG-08: When my boss provides me with helpful information about forthcoming changes affecting my work, he/she uses:
- ML-DG-09: When my boss provides me with helpful information about past changes affecting my work, he/she uses:
- ML-DG-10: When my boss shares news with me about organizational achievements and financial status, he/she uses:
- ML-EL-01: When my boss gives me praise for my good work, he/she uses:
- ML-EL-02: When my boss shows me encouragement for my work efforts, he/she uses:
- ML-EL-03: When my boss shows concern about my job satisfaction, he/she uses:
- ML-EL-04: When my boss expresses his/her support for my professional development, he/she uses:
- ML-EL-05: When my boss asks me about my professional well-being, he/she uses:
- ML-EL-06: When my boss shows trust in me, he/she uses:
- ML-MM-01: When my boss tells me stories about key events in the organization's past, he/she uses:
- ML-MM-02: When my boss gives me useful information that I couldn't get through official channels, he/she uses:
- ML-MM-03: When my boss tells me stories about people who are admired in my organization, he/she uses:
- ML-MM-04: When my boss tells me stories about people who have worked hard in this organization, he/she uses:
-

- ML-MM-05: When my boss offers me advice about how to behave at the organization's social gatherings, he/she uses:
- ML-MM-06: When my boss offers me advice about how to "fit in" with other members of this organization, he/she uses:
- ML-MM-07: When my boss tells me stories about people who have been rewarded by this organization, he/she uses:
- ML-MM-08: When my boss tells me stories about people who have left this organization, he/she uses:

The questions below were answered on a Likert-type scale ranging from "1 – Strongly disagree" to "5 – Strongly agree".

Job Satisfaction (SAT)

- SAT1: I am very satisfied with my current job
- SAT2: My present job gives me internal satisfaction
- SAT3: My job gives me a sense of fulfillment
- SAT4: I am very pleased with my current job
- SAT5: I will recommend this job to a friend if it is advertised /announced

Organizational Commitment (COM)

- COM1: I would be very happy to spend the rest of my career with this organization
- COM2: I feel a strong sense of belonging to my organization
- COM3: I feel 'emotionally attached' to this organization
- COM4: Even if it were to my advantage, I do not feel it would be right to leave my organization
- COM5: I would feel guilty if I left my organization now

Questions 1-8 below were answered on a Likert-type with the following options: (1) Bad, (2) Not Good, (3) Average, (4) Good, (5) Excellent
Question 9 was answered on a Likert-type with the following options: (1) Really Slow, (2) Slow, (3) Neither, (4) Fast, (5) Really Fast

Performance (PERF)

- JP1: Which of the following selections best describes how your supervisor rated you on your last formal performance evaluation
- JP2: How does your level of production quantity compare to that of your colleagues' productivity levels?
- JP3: How does the quality of your products or services compare to your colleagues' output?
- JP4: How efficiently do you work compared to your colleagues? In other words, how well do you use available resources (Money, people, equipment, etc.)?
- JP5: Compared to your colleagues, how good are you at preventing or minimizing potential work problems before they occur?
- JP6: Compared to your colleagues, how effective are you with keeping up with changes

that could affect the way you work?
- JP7: How well would you rate yourself compared to your colleagues in adjusting to new work changes?
- JP8: How well do you handle work place emergencies (such as crisis deadlines, unexpected personnel issues, resources allocation problems, etc.) compared to your colleagues?
- JP9: How quickly do you adjust to work changes compared to your colleagues?

The **demographic characteristics** questions below were not answered on a Likert-type scale.
- Age:
- Gender: (Male/Female options were provided)
- Education: (High School, 2-Year College, 4-Year College, Master's Degree, Doctoral Degree)
- Tenure: (Years of work at current organization)
- Work Experience: (Number of total years at work)
- Managerial Rank: (Junior staff, Senior staff, Junior manager, Middle-level manager, Senior-level manager)

Cultural manipulation check items

The questions below were answered on a Likert-type scale ranging from "1 – Of outmost importance to me" to "6 – Of very little or no importance." (All items were reversed in the instrument).

Masculinity/femininity (MF)
- MF1: In your ideal job, how important is it to you to have a good working relationship with your manager?
- MF2: In your ideal job, how important is it to you to have an opportunity for high earning?
- MF3: In your ideal job, how important is it to you to work with people who cooperate well with one another?

Individualism/Collectivism (IC)
- IC1: In your ideal job, how important is it to you to have a job which leaves you enough time for your personal or family life?
- IC2: In your ideal job, how important is it to you to have good physical working conditions (good ventilation and lighting, adequate work space, etc.)?
- IC3: In your ideal job, how important is it to you to have training opportunities (to improve your skills or to learn new skills)?

The questions below were answered on a Likert-type scale ranging from "1 – Very strongly agree" to "7 – Very strongly disagree". (All items were reversed in the instrument).

Power Distance (PD)
- PD1: Having an interesting work to do is just as important to most people as having

high earnings

- PD2: A corporation should have a major responsibility for the health and welfare of its employees and their immediate families
- PD3: How frequently, in your experience, do the following problems occur? Employees being afraid to express disagreement with their managers (1- Very frequently to 7- Very seldom)

Uncertainty Avoidance (UA)

- AU1: Company rules should not be broken, even when the employee thinks it is in the company's best interests "1 – Very strongly agree" to "7 – Very strongly disagree"
- AU2: In your current job, how often do you feel nervous or tense at work? ("1- Always" to "5- Never")
- AU3: In your current job, how long do you think you will continue working for this firm? ("1- Until I retire" to "4- Two years at the most")

The questions below were answered on a Likert-type scale ranging from "1 – Of outmost importance to me" to "6 – Of very little or no importance". (All items were reversed in the instrument).

Long-term/short-term orientation (LT)

- LT1: In your current job, how important the following item is it to you: Persistence (perseverance)
- LT2: In your current job, how important the following item is it to you: Thrift (ability to carefully manage material resources)
- LT3: In your current job, how important the following item is it to you: Patience?

Appendix C: Online Survey Snapshot

The Effect of Media Naturalness on Motivating Language

Study Title: The Effect of Media Naturalness on Motivating Language Investigators: James Cox, Dr. Ned Kock, Dr. Jacqueline Mayfield, Dr. Milton Mayfield.

James Cox is a Ph.D. student in International Business. His research is the area of supervisor-subordinate communications and the communication medium in which they are conducted. The data in this survey will be anonymously collected and statistically analyzed. Its results and analysis will be used by James Cox as part of his doctoral dissertation. It is recommended that you

Although the study will not benefit you directly, it might provide information on how to improve supervisor-subordinate communications.

The appropriate people and review boards (IRB) at Texas A&M International University have approved the study and its procedures. The study procedure involves nominal risk or harm to you. It involves answering a questionnaire regarding your job and the way in which your boss or supervisor communicates with you, as well as demographic information. Participating in this will take you approximately 15 minutes. You are free to ask any questions about the study, and are free to contact Dr. Ned Kock at ned.kock@tamiu.edu or James Cox at jocox@dusty.tamiu.edu if you have any further questions. Also, if you have any questions regarding the rights of research subjects, you may contact Dr. Jennifer Coronado, Chair of the Institutional Review Board for the protection of human subjects, at irb@tamiu.edu or at (956) 326-3060.

Your participation in this study is voluntary, and you are under no obligation to participate. You have the right to withdraw at any time during the period of this study. Your identity will not be revealed while the study is being conducted or when the study is reported or published.

By completing this survey, I consent to my participation in this study.

* Required

Mechanical Turk Worker ID *

Your answer

Age *

Your answer

Gender *

Male

Female

VITA

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Selected Peer-Reviewed Publications and Conference Proceedings

Jha, A., & Cox, J. (2015). Corporate social responsibility and social capital. *Journal of Banking & Finance, 60*, 252-270.

Cox, J. & Kock, N. (2017). The Moderating Effect of Media Naturalness on Motivating Language: Using MTurk for Data Collection *PLS Application Symposium, 22nd Annual Western Hemispheric Trade Conference,* Texas A&M International University, Laredo, TX, April 2017