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Towards More Efficient Behavioral Coding of Teamwork via Machine Learning

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TOWARDS MORE EFFICIENT BEHAVIORAL CODING OF TEAMWORK VIA MACHINE LEARNING

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ABSTRACT

Teams have been an integral part of organizational success for several decades and as such, researchers have sought to better understand all aspects of work teams. To better inform research and practice, Marks, Mathieu and Zaccaro (2001) advanced a theory and framework of team processes that has become a seminal piece in our field. Their theory proposed that ten team processes could be mapped on to three second order constructs (transition, action, and interpersonal phases). Mathieu and colleagues (2019) developed and validated a measure designed specifically to align with Marks et al. (2001) framework. While much needed, this measure is not without limitations, namely its self-report nature and associated subjectivity.

The current study proposes a means for overcoming those limitations by using machine learning to automate the Mathieu et al. (2019) measure. This study used traditional human coding methods to code data from three different sources to include teams across various contexts. Data was used from NASA HERA teams, medical teams, and student engineering teams. Then, the researcher trained various models using Natural Language Classifier software (provided through IBM Watson) to create an automated coding scheme. The results of this study are mixed. Using Natural Language Classifier, various models were trained and tested according to the Marks et al. (2001) framework. However, once tested, the accuracy of the model was not up to standard. This study provides a fruitful avenue for future research; the models can be refined by collecting further data and then retraining the models.

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CHAPTER ONE

OVERVIEW OF THE PRESENT STUDY

Introduction

Since before the turn of the century, organizations have shifted from classifying work around an individual job towards classifying around larger clusters of tasks assigned to teams (Ilgen, 1999). Teams have been an integral part of organizational success for several decades and as such, researchers have sought to better understand all aspects of work teams. Teams are formally defined as "a distinguishable set of two or more people who interact, dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission" (Salas, Dickinson, Converse, & Tannenbaum, 1992, p.4). A major area of teams' research that Industrial/Organizational Psychologists have explored is understanding the processes that employees use to work together (Marks, Mathieu, Zaccaro, 2001).

While much has been learned about teams in the workplace, there is still progress to be made in the science of teams and its application to practice (Tannenbaum, Mathieu, Salas, & Cohen, 2012). Historically, research has relied on studying small teams in highly controlled and low fidelity settings. However, this limits the generalizability of research findings to most team-based organizations which are (1) substantially larger in terms of membership and (2) engage in activities in complex operational environments (Tannenbaum et al., 2012).

Purpose of the Current Study

The purpose of the current study is to build upon work done by Mathieu and colleagues over the past several decades. Marks, Mathieu and Zaccaro (2001) advanced a theory and framework of team processes that has become a seminal piece in our field. Their theory proposed that ten first-order constructs would map to three second order constructs, a framework which will be explained in greater detail in a subsequent section. Until recently, there had been no known validated measure of the team processes identified in this widely cited taxonomy, although numerous researchers have leveraged the taxonomy to develop their own surveys and behavioral observation tools (LePine, et al., 2008). Recognizing the need for a unified metric, Mathieu and colleagues (2019) developed and validated a self-report survey tool designed specifically to align with the Marks et al. (2001) framework. This measure provides a common metric for team researchers and practitioners to use going forward but is not without limitations. The main goal of this study is to overcome those limitations, such as the self-report and time-consuming nature of the measure. More specifically, this research is designed to assess the potential to automate Mathieu et al.'s (2019) measure using natural language classification in IBM Watson to analyze text from team communications during simulated exercises across different contexts.

Contributions to Theory and Practice

Mathieu and colleagues (2019) advanced the teams literature by creating a survey measure of team processes based on the Marks et al (2001) framework. Survey responses are valuable indices of team processes, and there is no question that this survey measure was needed for our field. However, Mathieu and colleagues admit that alternative methods of measurement should be considered, either in place of, or to supplement their survey measure. Additionally, Kozlowski (2015) calls for researchers to seek supplement questionnaire-based assessments with alternative measures of behavior (p.285). The current study answers the need to explore alternative measures of team processes.

By creating an automated measure of team processes, this research seeks to minimize intrusiveness of traditional survey measures. The purpose would be to capture audio of a team and be able to feed transcriptions of the audio through the machine learning program. The machine will then automatically code the audio into the team process classification scheme. This project would aid practitioners who are interested in capturing team dynamics (with the intention to improve team processes) by saving them ample time and resources. Researchers will benefit from this study as well, as this project will bridge the gap between machine learning and psychology. This technology is at the tip of our fingers and should be leveraged to advance our field's measurement approaches.

CHAPTER TWO

THEORETICAL BACKGROUND: TEAM PROCESS TAXONOMY

Theoretical Background & Framework

This research seeks to develop an automated measure of team processes, based upon Marks et al. (2001) framework, which will be reviewed in detail here. Marks et al., (2001) defined team process as:

> member's interdependent acts that convert inputs to outcomes through cognitive, verbal and behavioral activities directed toward organizing taskwork to achieve collective goals…. Centrally, team process involves members interacting with other members and their task. They are the means by which members work interdependently to utilize various resources such as expertise, equipment, money, to yield meaningful outcomes (e.g., product development, rate of work, team commitment, satisfaction). (p. 357).

It is important to note that team process is different from taskwork, which is defined as "a team's interactions with tasks, tools, machines, and systems" (Bowers, Braun, & Morgan, 1997: 90). In other words, taskwork represents *what* teams are doing while teamwork describes *how* teams are doing it, and team processes are the means by which taskwork is achieved for goal accomplishment (Mathieu et al., 2001). Researchers in this area have been interested in understanding the how, or the teamwork. The focus of this study will also be centered around the teamwork, rather than the taskwork piece of this definition.

Temporal Dynamics of Teams

Time is inherently a factor which impacts work teams striving toward a collective goal (Locke & Latham, 1990). Team functioning is impacted by coordination of schedules, deadlines, and alignment of effort, just to name a few. Such time-based rhythms shape how team members manage their behavior to align efforts with others to get the job done. Mathieu and colleagues were the first to propose a dynamic model of team processes, while previous team effectiveness models included processes sans temporal influences. The approach taken by Marks et al. (2001) is to overlay their team process model onto the traditional Input-Process-Output (I-P-O) framework. They argued that different team processes occur at different phases of taskwork and that I-P-O relationships occur across synonymous cycles. The I-P-O framework has traditionally been viewed as static (McGrath, 1993), meaning only a single task is analyzed in isolation according to the I-P-O model. Teams are often tackling multiple tasks in a given performance period, which may overlap in terms of where they are in the I-P-O framework.

Team performance goals consist of several I-P-O cycles that occur sequentially and simultaneously (Mathieu et al., 2019). It is believed that teams perform in temporal cycles, deemed as "episodes" (Weingart, 1997; Zaheer et al., 1999). Mathieu and Button (1992) defined episodes as distinguishable periods of time over which performance accrues and feedback is available. Teams will undergo different processes depending on what point in the performance episode they are at. Below, the team process taxonomy (the focal point of this study) will be explored, and it will become evident how different processes are exhibited depending upon what phase of the performance episode the team is undergoing. The current study will also explore how using an automated measure of team processes will capture team dynamics over time, compared to traditional coding methods.

Team Process Taxonomy

Marks and colleagues (2001) developed a taxonomy of team processes with the intent that this framework would be broad enough to generalize across different types of teams. This framework is the most fitting for the current research project, as the measurement tool to be developed will also strive to be applicable to teams across different disciplines. This taxonomy is based on team process frameworks, such as those developed by Fleishman & Zaccaro (1992) and Prince & Salas (1993). However, this schema advances past work by incorporating a multiphase perspective of team processes. The taxonomic structure differs to include this temporal perspective, such that processes are nested within their respective transition and action phases. Again, this type of structure is the most fitting for this project because the research is interested in capturing team processes in real time, including within both action and transition phases of performance episodes.

Marks and colleagues (2001) developed their framework through a combination of reviewing research models and empirical studies in conjunction with integrating applied experiences with teams to generate process dimensions consistent with existing theory. It is presented as a hierarchical structure, where ten process dimensions are nested within three superordinate categories: transition phase processes, action phase processes, and interpersonal phase processes. Each of the ten process dimensions can be performed on a scale from complete skill to hardly any skill. Figure 1 displays the taxonomy with definitions, as will be explained in further detail below. See Marks, Mathieu, and Zaccaro (2001) for a full cross-reference of the dimensions with those of earlier taxonomic efforts.

Transition Phase Processes

Transition phases are defined as periods of time when teams focus on the evaluation of past activities or planning of future activities to guide their accomplishment of a team goal (Marks et al., 2001). As such, transition processes occur prior to, or between performance episodes. Within a transition phase, there are three primary processes: mission analysis formulation and planning, goal specification, and strategy formulation. Examples of when these processes might occur include staff meetings, retreats, and after-action reviews (Marks et al., 2001). Each process will be described in more detail below.

Mission analysis formulation and planning. Mission analysis is defined as “the interpretation and evaluation of the team’s mission, including identification of its main tasks as well as the operative environmental conditions and team resources available for mission execution” (Marks et al., 2001, p. 365). Before undergoing a mission, the team must interpret their capability for mission success based on internal and external constraints. These constraints may consist of team member abilities, resources, and time pressures. Also important during this process is to ensure all team members have a shared vision of the team’s purpose and objectives. A shared vision ensures that members will align their individual goals and efforts in pursuit of the superordinate team goal

(Mccomb, Green, & Compton, 1999). When mission analysis occurs in between performance episodes, it's imperative that the team engages in both backward evaluation of the past episode and forward visioning of the future episode. When teams diagnose previous performance and understand the successes and failures, they can better prepare their efforts for future performance (Blickensderfer, Cannon-Bowers, & Salas, 1997). Forward visioning can also help teams discuss contingency plans for how they would deal with uncertain circumstances or changing events. Failure to do so would put teams at risk when faced with dynamic situations, and likely would result in the team operating in a reactive mode. Teams that disregard mission analysis are more likely to allocate their attention and efforts to the wrong aspects of the task and will not realize until it's too late to recover (Gersick, 1988). Mission analysis is imperative for teams to engage in to have successful performance.

Goal specification. Goal specification requires a team to identify and prioritize goals and sub-goals for mission achievement (Marks et al., 2001). This process requires a discussion among team members to decide what the overall mission goals are, deadlines for sub-goals, and with what quality those goals will be attained. A classic example of this is a group project for undergraduate students where they must complete a task or experiment together and write a report and/or present their findings. The team must set a deadline for completing the task, assign roles as to who will complete what part of the task, and then divide up who will write what part of the report. This process occurs in the transition phase along with mission analysis and strategy formulation, and as such should occur in tandem with the other two processes. For instance, the strategy and goals of the mission should be aligned. As mentioned in the mission analysis process, teams should prepare contingency plans in case of unforeseen circumstances. However, in cases when the contingency plans won't suffice, teams may have to re-specify goals on the fly during an action phase.

Characteristics of effective goal specification include challenging yet attainable goals that align with the team's overall vision and mission (Marks et al., 2001). In contrast, ineffective goal specification may occur when the goals are too general or vague, are conflicting, are unattainable or impractical, or most importantly, are not valued by members of the team. If the goals do not resonate with the individuals, they are less likely to put effort towards them (Pearsall, & Venkataramani, 2015). It's important that there is a team discussion outlining the goals of the mission so everyone can have a shared understanding of them.

Strategy formulation and planning. Strategy formulation and planning involves developing alternative courses of action for mission accomplishment. Generally, this involves a group discussion about how team members will achieve their missions. More specifically, team members should discuss expectations, role assignment, and communication of plans to all team members (Hackman & Oldham, 1980; Stout, Cannon-Bowers, Salas, & Milanovich, 1999). Like mission analysis, strategy formulation involves consideration of internal and external constraints such as time constraints, resources, and member expertise (Marks et al., 2001). Teams today operate in complex and dynamic environments (Zaccaro, Rittman, & Marks, 2001) and will not be successful without a developed strategy (or multiple strategies) in place. Teams with ineffective strategies will rely on experience or make plans on the fly, which does not bode well for high-risk situations.

Marks and colleagues (2001) distinguished strategy formulation and planning further into three subdimensions: (1) deliberate planning, (2) contingency planning, and (3) reactive strategy adjustment. Deliberate planning is the formulation of a principal course of action for mission accomplishment. This should occur during transition phases before a performance episode. Deliberate planning is premeditated (Weldon, 1998) and is what is most thought of in reference to team planning, as evidenced by the team literature.

Next, is contingency planning, or forming alternative plans in response to potential or anticipated changes in the performance environment. Contingency planning was briefly mentioned in mission analysis, and the recurrence of this should emphasize how important this process is for teams. Teams should have specified alternative courses of action to use if needed, especially for those operating in highly dynamic or unpredictable situations. For instance, surgical and oncology teams may have contingency plans when operating on a tumor, since there is only so much that they know until the surgery is underway. Once the surgeons see the tumor firsthand, they may need to adjust how they will proceed with the surgery. Only having one plan and adapting on the fly would not be enough in this case, and there should be predetermined if/then scenarios in place. Contingency planning cannot always account for every variant of a situation. Thus, reactive strategy adaptation is a subdivision of strategy formulation that may occur when an unforeseen need emerges for strategic change (Marks et al., 2001).

Formally defined, reactive strategy adjustment is the alteration of existing strategy in response to unexpected changes in the environment, where neither the original nor contingency plans will suffice.

Action Phase Processes

Action phases, in contrast to transition, describe the behaviors that members engage in while working toward goal accomplishment (Mathieu et al., 2019). According to Marks and colleagues (2001), there are four processes that encompass action phases: monitoring progress toward goals, systems monitoring, team monitoring and backup responses, and coordination activities.

Monitoring progress toward goals. Monitoring progress toward goals is defined as "tracking task and progress toward mission accomplishment, interpreting system information in terms of what needs to be accomplished for goal attainment and transmitting progress to team members" (Marks et al., 2001, p. 366). Feedback is provided to the team on its goal accomplishment status in real time so that members are aware of their status and the likelihood that the team meets its collective goal. Self-regulation is defined as changing oneself based on standards, or ideas of how one should or should not be (Vohs & Baumeister, 2016). Monitoring progress serves as a means of self-regulation for the team, by alerting teams when performance gaps emerge so they can close the gap between their current performance and their desired performance state (Austin & Vancouver, 1996). Monitoring goals is more than detecting progress, but also relaying that information to other team members. For instance, in a flight crew team, the pilot may have more information about the progress than the co-pilot, and he or she must relay that information to the co-pilot and any other team members, so the team is on the same page.

Along with stating goal progress, team members may also suggest how they should alter their goals in order to meet their overall objective. As mentioned above, the self-regulation aspect of a team suggests that members will strive to close the gap between current performance and goal performance, such that they will think of ways to increase effectiveness and avoid obstacles (Gaddy & Wachtel, 1992). On the other hand, poor goal monitoring occurs when teams procrastinate, lose track of their objectives, or are altogether unaware of their progress and thus cannot gauge accurate feedback. Teams working in highly dynamic environments, such as surgical teams, will likely monitor their progress more frequently than a group of students working on a class project together. In fact, the group of students may even wait until periods of transition, rather than action phases, to discuss progress monitoring.

Systems monitoring. Systems monitoring is concerned with internal systems monitoring as well as external environmental monitoring. For instance, internal monitoring refers to tracking team resources (e.g., personnel, equipment, etc.) while environmental monitoring tracks external conditions relevant to team functioning (Marks et al., 2001). While this can certainly happen during transition phases, it is critical that members observe changes *as they occur* during an action phase. If a team is running low on a specific resource, it should be communicated to the team in situ rather than waiting until the next break in action, just like a pilot would relay a change in weather to their team in real time.

For teams to be effective in highly dynamic environments, progress must be monitored continuously. The rise of technology in the 21st century aids in systems monitoring. For instance, the multitude of machines in an operating room helps a surgical team to constantly monitor the state of the patient in pursuit of their goal (i.e., successful surgical operation). Any changes in the patient's vitals or condition are communicated to the team immediately so the members can adjust accordingly. Teams that do not have ever present technology may have set guidelines for when they take time to monitor conditions. For example, a construction team might have set times for when they check weather (Marks et al., 2001) such as before work and during their lunch break, so they can ensure their team is not exposed to dangerous elements.

Team monitoring and backup responses. Team monitoring and backup responses is described as helping members perform their tasks by (1) providing feedback or coaching to a team member, (2) behaviorally assisting a team member, or (3) assuming responsibility to complete a team member's task (Marks et al., 2001). For team backup to be effective, member's must be familiar or at least aware of one another's roles so they can identify when assistance is needed and how they can provide such. If team members aren't willing to help one another, then the team will likely fail if one member fails. While this could occur during a transition phase, with a team member expressing they may need extra help in the upcoming task, it is most important during an action phase. If a team member can adapt on the fly to help another member out when they are struggling, then the team will be much more likely to succeed. There may be unforeseen circumstances that render an individual unable to carry out their role, but with the help of a team member stepping in, the team's overall performance could be salvaged.

Coordination activities. Coordination is the process of orchestrating the sequence and timing of interdependent actions (Marks et al., 2001). For this to happen, team members must engage in information exchange and mutual adjustment to align actions with distal goal accomplishment (Brannick et al., 1993). Coordination occurs during both the transition and action phases of goal pursuit. When tasks are highly interdependent, teams will rely more heavily on coordination as a central process of team functioning (Tesluk, Mathieu, Zaccaro, & Marks, 1997). The more familiar team members are with one another, the more seamless their coordination will likely be (Espinosa, Slaughter, Kraut, Herbsleb, 2007).

Interpersonal Processes

The last three processes of this taxonomy belong to the interpersonal processes phase and consist of conflict management, motivating/confidence building, and affect management. Interpersonal processes occur throughout both transition and action phases. Interpersonal processes often foster the effectiveness of the other processes described above.

Conflict management. Conflict management is broken up into two different subdimensions. The first type is preemptive conflict management, defined as "establishing conditions to prevent, control, or guide team conflict before it occurs" while the second type, reactive conflict management involves "working through task, process, and interpersonal disagreements among team members" (Marks et al., 2001, p. 368). The way teams handle conflict will either hinder or boost productivity of the team.

Preemptive conflict management focuses on containing the conflict before it occurs, thereby setting norms when a team is first formed. These norms will help dictate how members handle conflict when it inevitably arises. A technique for controlling team conflict is setting up team contracts or charters that outline how conflict and difficult situations are to be handled (Smolek et al., 1999). In contrast, reactive conflict management pertains to techniques that will reduce conflict that emerges during a performance episode. Problem solving and compromise are examples of how one might handle conflict when it occurs unexpectedly.

Motivation/confidence building. Motivation and confidence building occur when team members strive to provide a sense of collective confidence and establish cohesion in pursuit of mission accomplishment (Marks et al., 2001). An example of this is commonly seen as pep talks to instill confidence in the team or encouraging team members to perform better. The opposite of this process involves negative comments about the team’s competence and can greatly derail the team’s performance. Such debilitating behaviors could even lead to social loafing, which occurs when motivation is low and individuals reduce the level of effort put forth into a task (Latane, Williams, & Harkins, 1979). Thus, team members with positive attitudes and beliefs can help envision success for the team and instill motivation to pursue the collective goal.

Affect management. Lastly, affect management refers to “regulating member emotions during mission accomplishment, including social cohesion, frustration, and excitement” (Marks et al., 2001, p. 369). Put simply, the purpose of affect management is to regulate team member emotions. Techniques to do so may involve boosting team morale, empathizing when someone is having a difficult time, calming others down in stressful situations, and controlling animosity among members, to name a few. Team building activities can assist with affect management by targeting emotion regulation. Additionally, by undergoing these activities, team members build interpersonal relations and become more familiar with one another. Members may feel more comfortable to joke, relax, or even complain which are all forms of affect management (Marks et al., 2001). It is important to implement affect management in a positive way, rather than promoting negative affect which could lead to performance decline.

Taxonomy Summary

The taxonomy put forth by Marks and colleagues (2001) offers a classification system that arranges ten processes into three higher-order dimensions. This is the best fitting model for the current research study, as it encompasses an array of processes that teams from different disciplines are likely to engage in. The teams used for this study are from different disciplines engaging in different tasks, and it will be interesting to see if the transition and action processes break down how they are framed in the current framework. As stated by Marks and colleagues, the lower order factors are most likely to occur in their respective phases, but this is not always the case.

CHAPTER THREE

ALTERNATIVE MEASURES/TECHNOLOGICAL ADVANCES

Drawbacks of Traditional Methodology

Traditional methodology of measuring team processes has largely been done via self-report measures or behaviorally anchored rating scales. While studying teams operating in situ, it has been particularly challenging to capture dynamics using our traditional methods (Klonek, Gerpott, Lehmann-Willenbrock, & Parker, 2019). Typically, our traditional methods are static, and to truly understand temporal contingencies of team dynamics, we need to use methods that do not interrupt team interactions and provide a high, movie like, temporal process resolution of teams (Kozlowski, 2015). For example, think of the current state of the methods, such as self-report measures, as providing merely “snapshots” of team dynamics. There is a great deal of important information that we can miss between snapshots of data we get, which is why pushing toward a measure that is deemed “high resolution” (Klonek et al., 2019) is critical. The subsections below will describe in detail the drawbacks of the current methodology and why researchers should move beyond implementing such measures.

Limitations of self-report measures. Self-report measures can be an efficient means to collect data but are also known for several issues. For instance, self-report measures have been criticized for their accuracy and the potential for responses being confounded with biases and social desirability (Arnold & Feldman, 1981; Taylor, 1961). In the interest of studying in-tact teams, especially teams in high-risk settings, it is extremely impractical to ask team members to fill out a survey. Furthermore, administering a survey post performance episode does not catch the team dynamics and processes in real time, but rather is relying on individual memories or perceptions to access such constructs. As a field, we need to push the science further to have better means for capturing teams in the wild.

Limitations of behaviorally anchored rating scales. Behaviorally anchored rating scales (BARS) could be another way to measure team processes and would even be able to display how well or poorly a team is engaging in each process. BARS provide a way to measure how an individual's (or team's) behavior in various categories contribute to achieving the goals of the team (Ohland et al., 2012). However, BARS are extremely time consuming to develop and are resource intensive. Subject matter experts must provide input for the instrument development and are typically more applicable for developing performance metrics for a specific job role (MacDonald & Sulsky, 2009). For the purpose of the current study, developing a BARS instrument would not be useful for trying to capture team processes in the wild. Thus, advanced and alternative methods are explored below.

Limitations of wearable sensors. In the age of big data, wearable sensors have begun to gain traction in organizational research. Wearable sensors are "mobile devices containing electronic components that record the environmental context of the device-bearing person" (Chaffin, Heidi, Hollenbeck, Howe, Yu, Voorhees, & Calantone, 2017, p. 4). Raw data from wearable sensors can be used to compute measures of low-level behavioral measures. For instance, body movement or verbal activity can be created since the wearable devices can track GPS and audio communication. However, this type of data is often rolled up to try and capture some composite measure, such as social networks. There is weak evidence to support construct validity for measures that are often derived from wearable sensors, such as social networks (Chaffin et al., 2017). Also, of concern, is that research using wearable sensors may begin to compute constructs based on the data, that are different than the meaning of the construct that already exists in the literature.

Limitations of Human coding. Video-based and observational methods of assessing team processes are useful in trying to capture team processes in the wild, however it is extremely challenging. Observational research is time and labor-intensive (Klonek, Meinecke, Hay & Parker, 2020) for several reasons. First, the observers must be well trained on an observation protocol, and then the actual observations themselves may take time. The limitations of human coding can be overcome by using professional software systems that can assist the researcher to consistently code behaviors over time. This will be explored greater in the following section.

Artificial Intelligence and Natural Language Processing/Classification Overview

Artificial intelligence. Klonek et al (2020) states that they are not aware of any existing technological solution that can currently fully address the challenge of capturing team dynamics in the wild. However, the following section will propose a solution and software that can overcome this problem. Artificial intelligence (AI) is formally defined as the concept that machines can be improved to assume some capabilities normally thought to be like human intelligence such as learning, adapting, self-correction, etc. (Kok, Boers, Kosters, Van der Putten & Poel, 2009). However, this is just one definition of AI out of many existing variations. AI can be thought of as a mindset, a way of looking at and solving problems from a point of view (Akerkrar, 2014). Some tasks that demand intelligence include (but are not limited to): speech generation and understanding, pattern recognition, mathematical theorem proving, and reasoning (Akerkar, 2014). A form of AI, machine learning, is used in the current study under the category of pattern recognition, where software will be trained to recognize certain keywords that belong to certain categories. IBM Watson is an AI tool that will assist in this research.

Machine Learning/Natural language processing. Natural Language Processing (NLP) techniques, which are also referred to as text analytics, infer the meaning of phrases by analyzing their syntax, context, and usage patterns (Ferrucci et al., 2012). More specifically, NLP explores how computers can be used to understand and manipulate natural language to do a variety of tasks (Chowdhurry, 2003). An example of NLP has been used in the healthcare context, where Wu and colleagues (2018) explored the capabilities of using NLP to assist clinicians to see if the program could perform faster or better than the humans. IBM Watson uses an NLP program called Natural Language Classifier (NLC), which allows users to classify text into custom categories. NLC combines advanced machine learning techniques to provide high accuracy of text classification. This program is the most appropriate for identifying teamwork processes because it is inherently a classification system. The purpose of the study is to replicate and automate a taxonomy, and by using a classification program, it will be fitting to be able to replicate human coding and ability to create a schema. NLC is used via IBM Watson to create the automated team process measure in this study.

Machine Learning and teams research. While limited, there have been several studies that have made strides in measuring teamwork using machine learning that are noteworthy to mention. Klonek and colleagues (2020) created a communication analysis tool to capture team dynamics. This is a form of AI or machine learning but is not quite the sophistication that NLC could get at. Kozlowski and Chao (2018) also propose team interaction sensors and computational modeling as unobtrusive measurement techniques and process-oriented research methods to advance teamwork science. This work is integral to our field, especially to help move closer toward capturing team dynamics in real time. However, computational modeling is labor intensive and not widely used by our field. The benefit of the research proposed here is that the NLC software is an easy, user friendly machine learning package to use that can help researchers interested in capturing team process dynamics.

Hypotheses

To advance the science of team science forward, NLC will be used in the current study to create a means of capturing team processes in the wild. As mentioned above, there have been some efforts in using AI and machine learning approaches to measure teamwork. However, the current study seeks to use machine learning to specifically measure team processes. The main interest of the study is to be able to replicate the Marks, Mathieu, and Zaccaro (2001) framework using a BARS approach with human coders.

Subsequently, NLC software will be used to create an automated version of the measure resulting in the following hypothesis:

Hypothesis 1a-b: (1a) NLC in IBM Watson will produce an automated measure of team processes based on the Marks et al (2001) framework and (1b) using NLC will produce a measure that will be just as accurate, if not more accurate than human coding.

Further, the methodological approach in this study considers teams in different contexts. The purpose of this automated measure is to be used for measuring *all* teams, not just teams of a specific context. Described in greater detail in the methodology chapter, data will be used from teams of three different contexts; thus, I propose:

Hypothesis 2: The processes in the Marks et al., (2001) model generated by NLC will be consistent across teams of different contexts.

This study also seeks to explore whether the Marks et al. (2001) framework is missing any important team process. Now that we have the capability to measure teams dynamically and in the wild, is it possible that there is something we are missing? The study will strive to replicate the framework exactly, but will be prepared to address any outlying data that does not fit into the predetermined codes, thus:

Hypothesis 3a-b: (3a) Using NLC, the Marks et al., categories will be replicated; (3b) all the behaviors in the data will be able to be coded into at least one of the processes in the Marks et al (2001) framework.

Independent researchers will be coding the data to create predetermined codes, based on the Marks et al. (2001) framework, that can be used to train the NLC software in IBM

Watson. Next, more data will be inputted to the NLC software to see if the trained machine can code raw data on its own. Simultaneously, researchers will code this raw data in order to compare human results to the results of the machine. Thus, I hypothesize:

Hypothesis 4: NLC will be able to produce a classification system of the data in less time than the human coders and will be just as accurate.

As mentioned throughout this paper, it is critical that we begin to capture team dynamics in situ rather than looking at static approaches. One way to do this is to look at how temporal influences impact team dynamics. Again, static approaches only provide a snapshot of this, and NLC software may be able to provide us with more. Specifically, it is hypothesized that NLC may be able to help map the ebb and flows of transition and action phases better than traditional approaches can, thus:

Research Question 1: Can NLC be used to better identify how dynamics change over time than traditional human coding approaches?

The following section will dive into the methodology portion of this research and explain exactly how the NLC will be trained and used in this study.

CHAPTER FOUR

METHODOLOGY

Overview

This section will detail the process from start to finish of how this study unfolded. At a high-level, archival data was transcribed and cleaned to allow for behavioral instances to be coded. Simultaneously, individuals were trained on the team process literature and coding procedures. The primary researcher, along with research assistants, learned the IBM Watson program and how to proceed once the human coding was completed. Codes were then inputted in the IBM Watson Natural Language Classifier program and results were analyzed.

Data Sources

Data was used from three different sources: medical teams, student engineering teams, and NASA HERA teams. All data was archival, IRB approved, and collected prior to the start of this project for various related research and observational studies. The data from the medical teams and the engineering teams was collected in audio and video format. The NASA HERA data was collected as chat data. Below, I'll explain the context in which the data was collected and why it was chosen to be included in the current study.

The medical team data was collected from ongoing simulations that occur monthly at a large, Southeastern healthcare system. The healthcare system has a prestigious simulation center with twenty-eight simulation rooms functioning as virtual hospital environments. This center also includes six debriefing rooms, and state of the art video and data capture systems for assessment purposes. This study used data from an operating room (OR) crisis simulation course. The purpose of this course is to replicate low frequency, high risk events that could occur in the OR. Participants in this simulation are healthcare workers who are not required but encouraged to participate in these trainings periodically. Participants are assigned to an OR team role where they perform surgery on a simulated patient. Then, a crisis occurs in the operating room where the team must work together to overcome the unexpected challenge, with the main goal of saving the patient's life. Each training session was randomly assigned a crisis scenario. For instance, one crisis scenario is a fire in the OR.

The next data source, student engineering teams, was a different type of learning simulation as compared to the medical teams. Clemson University undergraduate Engineering students were assigned a semester long group project in an introductory course. The students were randomly assigned to a group, and each group met (on average) eight times outside of class throughout the semester. Meetings outside of class were video recorded. This context was a much lower risk environment than the medical context, as there was no obvious unexpected conflict. However, there was motivation to work together effectively since the students were being graded on the final project outcome. The purpose of this engineering learning exercise is meant to simulate a real engineering design team experience, developed with input from practicing engineers and similar to what these individuals are likely to experience once they are on the job.

Lastly, the NASA teams data was collected at the University of Georgia as part of a broader NASA-sponsored research effort (Carter et al., 2019). The individuals in this data collection consisted of University of Georgia students as well as NASA Human

Exploration Research Analog (HERA) participants. Additional information regarding the broader purpose, structure, and selection process for HERA is publicly available via: https://www.nasa.gov/analogs/hera. In this study, four interdisciplinary teams (totaling 12 individuals) worked interdependently to solve a complex task. The hypothetical task was to support a human colony on Mars. This simulation has been used for other NASA-funded projects, and thus has demonstrated the utility in examining teamwork behaviors and risks that might arise in long duration exploration teams. Chat, video, and audio data was collected as part of this study to examine the intra- and inter- team interactions as it unfolds over time. This study also mimics a high-risk dynamic environment, where team members must work together toward their overarching shared goal.

The NASA data was already transcribed since it was chat data. The medical team and engineering student team data was not transcribed by the original researchers. Engineering student team data was transcribed using a transcription service, REV. The company can distinguish among multiple speakers, which was needed for this project. The final transcriptions from the third-party company were randomly spot checked to ensure accuracy and no major issues were found. The medical team data was transcribed by an undergraduate research assistant and then spot checked by a second researcher to ensure accuracy. No major issues were found.

Sample Sizes Across Context

Thirteen OR videos, totaling three and a half hours, were transcribed and included in coding. Eight engineering sessions, which totaled approximately nine and a half hours were transcribed and included in coding. Lastly, thirteen NASA chat transcripts (from approximately thirteen hours of sessions) were included in coding. Coders used these full, transcribed documents to identify instances of team process behaviors. As displayed in Table 1, 5,106 behavioral instances were coded and included for the Watson model. Tables 4-6 break down the data counts by class and context. As an overview, the behavioral example data counts for each context are as follows: engineering context = 2,649 codes; NASA context = 1,834 codes; OR context = 623 codes.

Codebook Development

A detailed coding manual was designed, which is a complex and iterative task (Kerig & Baucom, 2004). First, the team process taxonomy from Marks and colleagues (2001) was adapted as the coding scheme to form the basis of the codebook. Several definitions of each process were included, as well as using language that would be digestible for coders. Examples were then pulled from existing data to map on to each team process as a guide for the coders to refer to.

Coding process. Four researchers were chosen and trained as coders based on the coding manual and team process literature. The coders consisted of two undergraduate research assistants and two graduate research fellows. All were compensated for their time and effort. The first step of the training process was to have coders read and learn the Marks et al. (2001) framework. Once they were familiar with the framework, they could move forward with learning the coding manual and BARS process. Then, each coder was given the same two sets of sample data, one set from the engineering context and one set from the NASA context. The reason these two contexts were chosen as sample data was because the NASA chat data was a unique format in excel, whereas the engineering and medical context were both word document transcriptions. After reviewing their agreement with the engineering transcripts, it was decided that if they were comfortable coding one type of the word document transcript, that they would be prepared to code the other context which used word documents. Therefore, they were not given a medical sample for training, just the engineering and NASA sample.

Once the research assistants finished coding the sample data, I calculated initial interrater agreement following the recommendations by LeBreton and Senter (2008). Interrater agreement was not acceptable, so consensus meetings were held to go over the discrepancies and come to 100% agreement. The purpose of the consensus meeting was to ensure that researchers were essentially interchangeable and on the same page when coding the behavioral process examples. After the consensus meetings, researchers were given data across all three contexts to independently code. They identified each example as a teamwork process and recorded it on a tracking sheet. Once the original coders completed coding their data sets, two other coders (who also completed the coder training outlined above) independently provided their own classes for the data sets. A minimal amount of discrepancies was found among the codes, and any that were found were investigated by the primary researcher.

This study involved a two-stage process. The first was the initial coding of transcripts to tag behaviors (i.e., identify unique segments that could be used for the training and testing of NLC models). The step was guided by BARS scales but did not address the ratings (quality) of the behaviors. In this first stage, it was a priority for the coders to identify each behavior and the subsequent accuracy of NLC in distinguishing that behavior.

The second stage focused on expanding the coding to examine the quality of behaviors. This was decided based on the first phase results. The behaviors for which NLC demonstrated the highest accuracy were then further coded. The highest accuracy from phase one results were those behaviors belonging to the Strategy Formulation category. This round of coding involved using a traditional BARS coding scheme to provide the quality rating, and then seeing if NLC could produce quality ratings once the model was trained. See Appendix B for BARS coding schema.

IBM Watson NLC training. The coded transcripts were cleaned and formatted according to guidelines for using Watson's NLC program. A last review of coding was conducted during the final formatting process by a SME, prior to training Watson. To address the hypotheses, six different models were created in IBM Watson's NLC program. Eighty percent of the codes were used for training, while twenty percent of codes (randomly selected) were saved for testing. An overarching table that summarizes each of the six models described below can be seen in Table 2.

The first model was an overall model that included codes which came from all three contexts. All codes were combined from the three contexts, so for example the "mission analysis formulation and planning" class for this model had codes from the engineering, NASA, and OR samples. To build this model, ten classes were created. Each class was a team process from the Marks et al. (2001) framework. Then, the relevant codes were uploaded to each matching class. The ten-class model was then trained by

IBM Watson's deep learning techniques and ready for testing. Test data was uploaded to the model to assess how well the model would perform. The test data was coded by the research assistants, so it did have classes attached to each code. However, when uploaded into Watson, it was uploaded without codes to see how accurate Watson could match the codes already provided by the raters.

This process was repeated three more times to build all models needed for this study. The second model was a three-class model, where I looked at the data from a higher level. I used codes for transition, action, and interpersonal phases to build this model. Even though the codes were originally coded into the specific teamwork process, using the Marks et al. (2001) framework it was possible to roll these lower level codes up into their respective higher order grouping. For example, mission analysis formulation and planning, goal specification, and strategy formulation belong in the transition phase. Codes from those three processes were used to build the transition class in the model.

The third, fourth, and fifth model separately tested the different contexts (i.e., engineer, NASA, and OR contexts). The purpose of running these models was to see if a specific context held up better for coding and NLC accuracy. Since the data came from teams operating in different environments, this research sought to investigate if there was any significant difference among the contexts. Each model was built out just as the first model was, with the ten classes. Codes that were identified for each process per each context were uploaded accordingly. The last model was an exploratory model. This model investigated the traditional BARS coding and sought to replicate rating behaviors on a scale of 1-5 (explained in further detail in Appendix B). In this case, the ratings were as follows: 5 = Complete Skill, 4 = Very Much Skill, 3 = Adequate Skill, 2 = Some Skill, 1 = Hardly Any Skill. The model had five classes, one for each rating of skill. Codes were used from the Strategy Formulation category since this category had the best accuracy from the overall model results. Codes were inputted according to class and then trained by IBM Watson, and ready for testing. The results for each model are presented in the following chapter.

NLC Algorithm. NLC in IBM Watson uses Convolutional Neural Networks (CNNs) to extract numerical features from the input text (training codes). The system then uses support vector machines (SVMs) to classify a text based on those numerical features. During a training phase, a CNN automatically learns the values of its filters based on the task you want it to perform (Kim, 2014). In the context of NLC, this means that the CNN automatically learns the values of each class based on the assignment of codes. SVMs are used to then determine how frequently that value appears in each class. Conneau, Schwenk, Barrault, and Lecun (2016) dive deeper in this topic and explore how machine learning algorithms are used in natural language processing programs. The parameter in the NLC was not altered but could be further investigated in future research efforts, to determine if changing parameters of the models will produce varying results.

CHAPTER FIVE

RESULTS

Model 1 Results. The first model tested was the ten-factor model of team processes across all contexts. Table 3 displays the detailed counts of how many text samples were used for the training and testing of this model; table 4 displays the cross-classification results. The accuracy of this model was tested against the human codes that already existed for the test text samples. To clarify, 80% of the codes from raters were used to train the model, and 20% were used to test the model. Thus, that 20% still had codes tied to the samples, but the codes were not inputted into Watson, just the text samples. From there, I calculated accuracy by comparing what Watson rated those text samples versus what the coders rated the text samples as. The accuracy results are as follows: *mission analysis formulation and planning, 17.46% accuracy; goal specification, 18.95% accuracy; strategy formulation, 52.05% accuracy; monitoring progress toward goals, 5.00% accuracy; systems monitoring, 11.46% accuracy; team monitoring and backup behavior, 9.82% accuracy; coordination, 25.42% accuracy; conflict management, 0.00% accuracy; motivation and confidence building, 6.90% accuracy; and affect management, 10.53% accuracy.* The NLC in IBM Watson was able to produce an automated measure of team processes based on the Marks et al (2001) framework, thus Hypothesis 1a is supported. However, using NLC did not produce a measure that was more accurate than human coding, thus Hypothesis 1b is not supported.

Model 2 Results. The results of Model 1 did not turn out as planned, so the next step was to investigate this model further. I looked at this model from the second order factors each process belonged to, to see if the higher order factors could be replicated. Tables 5 and 6 show the data counts and results in detail. The results from this three-factor model are as follows: *transition, 73.78% accuracy; action, 47.61% accuracy; and interpersonal, 9.20% accuracy.*

Model 3 Results. Model 3 attempted to replicate the ten-factor model of codes belonging only to the engineering context. Tables 7 and 8 show the data counts and results in detail. The results are as follows: *mission analysis formulation and planning, 23.81% accuracy; goal specification, 98.70% accuracy; strategy formulation, 51.47% accuracy; monitoring progress toward goals, 0.00% accuracy; systems monitoring, 18.18% accuracy; team monitoring and backup behavior, 6.67% accuracy; coordination, 35.88% accuracy; conflict management, 14.28% accuracy; motivation and confidence building, 11.11% accuracy; and affect management, 0.00% accuracy.*

Model 4 Results. Model 3 attempted to replicate the ten-factor model of codes belonging only to the NASA context. Tables 9 and 10 show the data counts and results in detail. The results are as follows: *mission analysis formulation and planning, 0.00% accuracy; goal specification, 11.76% accuracy; strategy formulation, 19.35% accuracy; monitoring progress toward goals, 21.88% accuracy; systems monitoring, 57.84% accuracy; team monitoring and backup behavior, 20.45% accuracy; coordination, 38.46% accuracy; conflict management, 16.67% accuracy; motivation and confidence building, 0.00% accuracy; and affect management, 70.37% accuracy.*

Model 5 Results. Model 5 attempted to replicate the ten-factor model of codes belonging only to the OR medical context. Tables 11 and 12 show the data counts and results in detail. The results are as follows: *mission analysis formulation and planning, 0.00% accuracy; goal specification, 0.00% accuracy; strategy formulation, 0.00% accuracy; monitoring progress toward goals, 0.00% accuracy; systems monitoring, 41.86% accuracy; team monitoring and backup behavior, 26.09% accuracy; coordination, 48.48% accuracy; conflict management, 0.00% accuracy; motivation and confidence building, 0.00% accuracy; and affect management, 25.00% accuracy.* NLC was able to replicate across different contexts but was not consistently accurate across all three contexts. It was most accurate across the engineering and NASA contexts; thus Hypothesis 2 is not supported. Overall, the Marks et al. (2001) categories were replicated, and all behaviors in the data were coded into at least one of the processes in the Marks et al. (2001) framework, thus Hypotheses 3a-3b were supported. There were no codes that seemed to fit into a miscellaneous category, so it is confirmed through this data that the Marks et al. (2001) is comprehensive across different contexts and there is not some behavioral category missing from their framework.

Model 6 Results. Model 6 sought to replicate a BARS rating model. I investigated whether a model could be trained to separate codes that were rated on a scale of 1(Hardly Any Skill)-5(Complete Skill). The data was analyzed from the Strategy formulation class from Model 1. The specific data counts and results can be seen in Tables 13 and 14. The results are as follows:

Hardly Any Skill, 28.57% accuracy; Some Skill, 14.29% accuracy; Adequate Skill, 46.15% accuracy; Very Much Skill, 0.00% accuracy; and Complete Skill, 25.00% accuracy.

Human versus Machine Coding Results. To address Hypothesis 4, I investigated whether NLC software was able to produce a classification system of the data in less time than the human coders, and if it would be just as accurate. The best approach to test this was to look at an engineering specific transcription, since the engineering context model performed the best compared to other contexts. There were three steps to this process. First, I coded the engineering transcript to produce "ground truth" results of how the behaviors should be coded according to the Marks et al. (2001) framework. Then, a research assistant coded the same transcript to provide the human coded results. Lastly, the transcript was inputted into Watson's NLC program, in the engineering context model that had already been trained.

The data counts can be seen in Table 15. The detailed results are displayed in tables 16 and 17. The results for machine accuracy are as follows: *mission analysis formulation and planning, 0.00% accuracy; goal specification, 31.58% accuracy; strategy formulation, 31.58% accuracy; monitoring progress toward goals, 0.00% accuracy; systems monitoring, 31.37% accuracy; team monitoring and backup behavior, 10.00% accuracy; coordination, 17.92% accuracy; conflict management, 100.00% accuracy; motivation and confidence building, 28.57% accuracy; and affect management, 33.33% accuracy.*

The results for human accuracy are as follows: *mission analysis formulation and planning, 50.00% accuracy; goal specification, 36.84% accuracy; strategy formulation, 50.00% accuracy; monitoring progress toward goals, 7.69% accuracy; systems monitoring, 62.75% accuracy; team monitoring and backup behavior, 50.00% accuracy;*

coordination, 16.47% accuracy; conflict management, 100.00% accuracy; motivation and confidence building, 52.38% accuracy; and affect management, 50.00% accuracy. NLC software was able to produce a classification system of the data in less time than the human coders but was less accurate; thus Hypothesis 4 was partially supported. These results will be discussed further in the final chapter.

CHAPTER SIX

DISCUSSION

Summary of Findings

Overall, the results of this study are mixed, but are an important first step in moving towards machine learning for team process measurement. A summary table of text that was coded and agreed upon by both Watson and human coders can be found in Table 18. Hypothesis 1a was supported, since it is possible to create an automated measure of team processes in the NLC software in IBM Watson. However, Hypothesis 1b was not supported; NLC did not produce a measure that was as accurate as human coding. Hypothesis 2 was not supported; the NLC software did not produce models consistent across teams of different contexts. The program was, however, able to produce three different models, one for each context. The issue was the accuracy of these models, which is why Hypothesis 2 is not fully supported. Hypothesis 3a and 3b were supported. Through the NLC software, the ten team processes were able to be replicated. All the behaviors in the data set were able to be coded into at least one of the processes in the Marks et al. (2001), and no behavior was coded into two different categories. Hypothesis 4 was partially supported. Although the machine produced a classification system of the data in much less time than human coders, it was not as accurate. As noted in Research Question 1, it was posed that NLC might better note how dynamics change over time. It is telling that the Engineering data had the highest percentage accuracy, since that data came from 2-hour team meetings and the teams met about eight times over the course of a semester. This could indicate that the longer the team is together, the processes become more distinguishable. The different team contexts are explored in more detail below.

Implications of Findings

Upon analyzing Model 2, it was clear that the transition phase had the highest percentage of accuracy compared to the other phases. This could signify that the data used in this study was heavily skewed toward transition phase processes. For example, the engineering data may have been mostly transition phase data since the student meetings centered around making plans for their project and working through goals, and how those goals would be achieved. Action phase data had almost fifty-percent accuracy, which seems to be due to the NASA and OR data. In the NASA context, they are working in real time to solve problems and achieve a goal, so they are mostly working in an action phase but theoretically should have quick transition phases in between each action period. The OR data is almost entirely one action phase, since a crisis occurs, and the data is recording participants solving the crisis. Across all three contexts, interpersonal phases had extremely low accuracy. This intuitively makes sense, because there was the least amount of training and test data for the interpersonal phase. There were minimal examples for the OR context, likely because there was not time to have interpersonal interactions since the participants were just working with the crisis at hand. Between the NASA and engineering context, there still were not many interpersonal examples. It makes sense that there were more for the NASA context since the data came from distributed teams, so the participants likely had to engage in more interpersonal connections.

Limitations

Overall, it is difficult to distinguish why the results didn't turn out as hoped, but there are several thoughts and limitations as to why that might be. First, it might be due to the coders not being team research experts. They were trained according to the Marks et al. (2001) framework and the BARS codebook, but prior to this study they did not have any teams research background. The machine accuracy results are based on what the coders originally classified each text sample as, so if the text sample itself was not coded right, then the comparison would be inaccurate. Furthermore, the machine was trained based on human codes. If there was human error in the original codes, then there is going to be error in the machine measure. The codes were spot checked by the primary researcher, but there were over 5,000 codes, meaning there was room for error. Another thought is that the data used could have limited the machine's accuracy. The engineering data was great data to use for this project, since each transcript was about two hours long and recorded a team working meeting from start to finish. I think that this type of data was best designed to capture team processes. The NASA chat data dealt with distributed teams and was not in person meetings. This may not have captured the team processes correctly. The OR data, as mentioned above, was just a snippet of an action phase. Lastly, a potential reason for the machine's poor accuracy may just be the simplest answer; there was not enough data used. Even though approximately 4,000 codes used to train the machine, and 1,000 used for testing, to increase precision it could be that more data needs to be used.

Future Research

Future research should strive to build upon the model that has already been created in IBM Watson. The model can be further refined through "retraining", which means more data would need to be coded and then inputted into each class. This is an iterative process; after more data is coded and uploaded to a respective class in the model, then it would need to be tested to see if accuracy improved. Based on the results from the current study, it would be advised that data like the engineering data should be used. This type of data follows a team from start to finish, and captures long meetings where transition, action, and interpersonal phases would take place. On the other hand, it might be best to use data from a controlled laboratory study that elicits each of the ten phases. The data used in this study captured teams in the wild. While the goal for this measure would be to analyze data from teams in the real world, the training data might need to come from a controlled setting. Using the real-world teams for the training data could have been an issue and set the model up to fail. By using laboratory data, we could manipulate the task, so teams are required to engage in all ten processes. Then, that data would be coded and uploaded to create a new model (or retrain the old model) to have a solid framework. Then, data that comes from teams in field settings could be tested to see how it fits in the framework.

Related to this, it will be important to explore whether the Marks, Mathieu, and Zaccaro (2001) framework holds up in the real world. By collecting/using more data, we would be able to get a clearer picture of whether the model is as robust in the wild as it has been in laboratory settings. As has been discussed, the teams from three different differed in the types of processes they engaged in. By collecting data across more contexts, it can further explore this question.

Additionally, it would be interesting to explore the current data in further detail. One area of low hanging fruit to examine is the 80/20 splits of data. In this research, random 80/20 splits were used to classify training (80%) versus testing (20%). The low accuracy of the results may be due to the idiosyncratic nature of this random split. It would be worthwhile to consider additional random splits and aggregate the accuracy. Lastly, it would be interesting to see the cadence of the team process codes. This is also another area that could be explored in the short term with the current results. A next step for this project will be to explore the pattern of how team processes emerge based on the machine coding. The potential of Watson and NLC is endless, and future research should make every effort to get this model refined so that it can be used by both researches and practitioners alike to advance our science.

Conclusion

Understanding team processes is fundamentally important to help improve team performance (Klonek, Gerpott, Lehmann-Willenbrock, & Parker, 2019). Marks et al. (2001) advanced a theory and framework of team processes in their seminal piece at the turn of the century. Almost two decades later, Mathieu and colleagues (2019) developed and validated a survey measure of team processes. This framework and measure significantly advanced the team literature. However, as a field we should strive to move away from solely depending on self-report measures. Not only are they time consuming, but they are easily fakeable (Furnham & Henderson, 1982). Thus, the current research sought to develop an automated measure of team processes. The aim of this project was to contribute greatly to practice and theory alike, while aligning teams research closer with technological measurement advances. While the results did not turn out as hypothesized, it brings our field a step closer to automating a measure of team processes. More data points will help make the Watson measure more precise and can assist in future research efforts that hope to use this measure as a means of capturing team processes.

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APPENDICES

APPENDIX A

TEAM PROCESS MEASURE (MATHIEU ET AL, 2019)

Transition Processes

To what extent does our team actively work to…

Mission Analysis

1. Identify our main tasks?

2. Identify the key challenges that we expect to face?

3. Determine the resources that we need to be successful?

4. Develop a shared understanding of our purpose or mission?

5. Understand the needs of our primary stakeholders (e.g., customers, top management, other organizational units)?

Goal Specification

6. Set goals for the team?

7. Ensure that everyone on our team clearly understands our goals?

8. Link our goals with the strategic direction of the organization?

9. Prioritize our goals?

10. Set specific timelines for each of our goals?

Strategy Formulation and Planning

11. Develop an overall strategy to guide our team activities?

12. Prepare contingency ("if-then") plans to deal with uncertain situations?

13. Know when to stick with a given working plan, and when to adopt a different one?

14. Periodically re-evaluate the quality of our working plans?

15. Specify the sequence in which work products should be accomplished?

Action Processes

To what extent does our team actively work to ...

Monitoring Progress Toward Goals

16. Regularly monitor how well we are meeting our team goals?

17. Use clearly defined metrics to assess our progress?

18. Seek timely feedback from stakeholders (e.g., customers, top management, other organizational units) about how well we are meeting our goals?

19. Know whether we are on pace for meeting our goals?

20. Let team members know when we have accomplished our goals?

Systems Monitoring

21. Monitor and manage our resources (e.g., financial, equipment, etc.)?

22. Monitor important aspects of our work environment (e.g., inventories, equipment and process operations, information flows)?

23. Monitor events and conditions outside the team that influence our operations?

24. Ensure the team has access to the right information to perform well?

25. Manage our personnel resources?

Team Monitoring and Backup

26. Develop standards for acceptable team member performance?

27. Balance the workload among our team members?

28. Assist each other when help is needed?

29. Inform team members if their work does not meet standards?

30. Seek to understand each other's strengths and weaknesses?

Coordination

31. Communicate well with each other?

32. Smoothly integrate our work efforts?

33. Coordinate our activities with one another?

34. Re-establish coordination when things go wrong?

35. Have work products ready when others need them?

Interpersonal Processes

To what extent does our team actively work to ...

Conflict Management

36. Deal with personal conflicts in fair and equitable ways?

37. Show respect for one another?

38. Maintain group harmony?

39. Work hard to minimize dysfunctional conflict among members?

40. Encourage healthy debate and exchange of ideas?

Motivating and Confidence Building

41. Take pride in our accomplishments?

42. Develop confidence in our team's ability to perform well?

43. Encourage each other to perform our very best?

44. Stay motivated, even when things are difficult?

45. Reward performance achievement among team members?

Affect Management

46. Share a sense of togetherness and cohesion?

47. Manage stress?

48. Keep a good emotional balance in the team?

49. Keep each other from getting overly emotional or frustrated?

50. Maintain positive work attitudes?

APPENDIX B

TEAM PROCESS CODEBOOK

Coding Overview

Thank you for serving as a coder on this project. If at any time you have questions about a particular rating or the process as a whole, please do not hesitate to contact Dr. Shuffler or Michelle Flynn. We are interested in examining how team processes emerge in real-world team interactions. Ultimately, we will be using these ratings to inform a machine learning algorithm that will be able to automatically code these team processes after training. We will also use your ratings to compare the value and accuracy of human coding versus machine coding.

Coding Instructions

1. **Use the coding Excel sheet to track the coding you have done.**
    a. Keep a copy that is your own that you can edit but make sure to keep it backed up to a master copy on the shared drive.
2. **Every time you sit down to code, first go back and review all of the BARS descriptions as well as the instructions regarding distinguishing between transition and action phases. Because the task is a planning task, it is important to understand how we define and distinguish action and transition phases.**
    a. Many behaviors may fit the definitions of both transition and action phases. It is important to look at each behavior in the context in which it occurred before deciding whether or not it occurs in a transition or action phase.
    b. Refreshing every time you start coding will help make sure that you are consistently rating teams in the same way.
3. **Once you have refreshed on the coding scheme, choose a session to code.**
    a. Use the Google Doc called "BARS Team Processes Codebook" to find what sessions you should be coding.
    b. Make a note in the Status column when you start and finish a session so we can keep track of progress. Also note the date completed when you finish.
    c. Please try to code each session in one sitting
4. **Read then entire transcript first, and make initial notes on how you would code each process behavior**
5. **Go back through the session and make ratings for each round for each of the teamwork behaviors, making any notes regarding questions or comments you may have.**
6. **If you have any questions while coding, please ask! It is better to get clarification while you are in the middle of coding as opposed to waiting and saving up a lot of questions all at once. Stop by, call, or email Marissa if you have any questions.**
7. **We will be checking for reliability halfway through the coding, so once you have about 15 sessions coded, let Michelle know.**

VARIABLES TO RATE

Transition Processes

1. Mission analysis formulation and planning
2. Goal specification
3. Strategy formulation

Action Processes

4. Monitoring progress toward goals
5. Systems monitoring
6. Team monitoring and backup behavior
7. Coordination

Interpersonal Processes

8. Conflict management
9. Motivation and confidence building
10. Affect management

How to Distinguish Action & Transition Phases

<table>
<tr><th></th><th>Transition</th><th>Action</th></tr>
<tr><td>Definitions</td><td>

“Periods of time when teams focus primarily on evaluation and/or planning activities to guide their accomplishment of a team goal or objective (Marks, et al., 2001).”
In the context of Democracy 2, transition phases involves:

Making evaluative statements regarding resources to generate goals
Creating goals and the strategies that will lead to successful goal completion
Creating a shared understanding of information available in order to make decisions

Behaviors:

Mission Analysis, Goal Specification, Strategy Formulation

</td><td>

“Periods of time when teams are engaged in acts that contribute directly to goal accomplishment (i.e., taskwork; Marks, et al., 2001).
In the context of Democracy 2, action phases involve:

Making declarative statements regarding information and resources
Gathering information from documents, the game, etc.
Making actual changes within Democracy 2
Sharing information related to implementing actions/decisions (e.g., changing policies, canceling policies)

Behaviors:

Monitoring Progress Towards Goals, Systems Monitoring, Monitoring Team Members/Backup Behavior

</td></tr>
<tr><td>How Do I Know Which One is Which?</td><td>

Is information being evaluated in regards to its importance, relevance, value?
Are questions being asked about how to reach goals (e.g., “so how do we get re-elected/make people happy/fix our budget”)?
Are questions being asked about what the main tasks are?

</td><td>

Is information being collected from the binders or game?
Is a team member specifically requesting help with performing a task?
Is information regarding how to perform a task being shared?

</td></tr>
</table>

Quick Tips for Distinguishing Behaviors

Behavior	What to Keep in Mind
1. Mission Analysis	1. What are all the possible things we can be doing?
2. Goal Specification	2. What are we actually going to do?
3. Strategy Formulation	3. How are we going to do it?
4. Monitoring Progress Towards Goals	4. What information tells us we are achieving our goals?
5. Systems Monitoring	5. What information is new or changed in regards to our overall mission?
6. Team Monitoring/Backup Behavior	6. How can I help you, or how can you help me?
7. Coordination	7. Who should be doing what, and when?
8. Conflict Management	8. Why can't we all just get along?
9. Motivating/Confidence Building	9. We can do it!
10. Affect Management	10. How can I cheer you up?

MISSION ANALYSIS

Definition: Interpretation and evaluation of the team's mission, including identification of the mission's main tasks as well as the operative environmental conditions and team resources available for mission execution.

Examples:

- Identification of available resources (political capital, money, etc.) for the team
- Creating an understanding of the teams' overall mission and overarching goals (get re-elected and maintain a balanced budget) and how unique information is distributed among team members in individual handouts
- Properly identifying the main tasks and environmental contingencies (i.e. situations, prime ministers, etc.)
- Prioritizing the mission objectives and required tasks

Scale:

Complete Skill (5) – Prior to the start of task, team members established all of the team's roles and task responsibilities; they also establish their individual contribution to the overall mission. They engaged in asking questions about what should be done during the course of their task and identified available resources.

Very Much Skill (4)

Adequate Skill (3) - Team members established their team and individual roles and task responsibilities, but did not establish how these things contributed to the overall mission. Questions asked were not necessarily evaluative. Team members were able to identify available resources but were confused as how to utilize them.

Some Skill (2)

Hardly Any Skill (1) - Team members did not establish their team and individual roles or task responsibilities; nor did they establish the individual or team's contribution to the overall mission. They had no idea what their mission objectives were, were confused, and did not ask any clarification questions to one another.

GOAL SPECIFICATION

Definition: Identification and prioritization of goals and sub-goals for mission accomplishment.

Examples: -

- Developing and assigning sub-goals that help the team accomplish mission objectives
- Developing and assigning goals for each individual in the team
- Prioritizing the goals developed by the team

Scale:

Complete Skill (5) – Members of the team agreed upon specific long-term and short-term goals to aid in directing the action of the team. Goals were prioritized and understood by all team members.

Very Much Skill (4)

Adequate Skill (3) - Members of the team prepared long-term and short-term goals to aid in directing the action of the team, but they were not specific. Goals were not fully understood, or some unresolved disagreement existed concerning whether or not the goals were useful.

Some Skill (2)

Hardly Any Skill (1) – No long-term or short-term goals were generated by the team. This caused confusion concerning what the team was trying to accomplish.

STRATEGY FORMULATION & PLANNING

Definition: Formulation of strategies and courses of action for mission accomplishment. This dimension includes generic planning, contingency planning, and reactive strategic adjustment.

Examples: - Communicating the proper sequence of actions to team members
- Considering factors that might alter their mission plan
- Recognizing and adjusting team actions or responsibilities to adapt to unexpected events (e.g., situations arising)
- Engaging in contingency planning consisting of verbally walking through "what if" scenarios which might emerge while playing

Scale:

Complete Skill (5) – Team members developed a primary course of action for achieving the team's goals and were able to detect and quickly adapt/coordinate their actions to unexpected situations with appropriate actions. The team tested and strengthened its plan using "what if" scenarios. All team members were aware of and understood how their individual task responsibilities fit into the primary and secondary courses of action.

Very Much Skill (4)

Adequate Skill (3) - Team members had difficulty developing a primary course of action for achieving the team's goals. The team briefly tested and its plan using "what if" scenarios. All team members were aware of their individual task responsibilities but might not have understood how they fit into the primary and secondary courses of action.

Some Skill (2)

Hardly Any Skill (1) –Team members did not develop a primary course of action for achieving the team's goals. Instead, they simply changed things within the game and saw what happened. The team did not plan ahead for potential scenarios which might emerge. Team members were unaware of their individual task responsibilities and how they fit into the primary and secondary courses of action.

MONITORING PROGRESS TOWARDS GOALS

Definition: Tracking task and goal progress toward mission accomplishment; reporting system information in terms of what needs to be accomplished for goal attainment, transmitting team goal progress to team members.

Examples:
- Tracking the team's progress on goals and subgoals (e.g., increasing specific constituencies, eliminating specific situations)
- Reporting the team's progress on goals and subgoals (e.g., increasing specific constituencies, eliminating specific situations)

Scale:

Complete Skill (5) – Maintained awareness of and tracked progress on their primary and secondary goals throughout the mission. Understood which individual tasks and responsibilities were necessary for goal attainment and established benchmarks to monitor these tasks.

Very Much Skill (4)

Adequate Skill (3) - Maintained awareness of and tracked progress on their primary and secondary goal progress throughout parts of the mission. Did not understand how individual tasks and team responsibilities fit into goal attainment.

Some Skill (2)

Hardly Any Skill (1) – The team is either "monitoring everything" or hardly anything at all. There is little connection between what the team is monitoring and the goals that they should be trying to accomplish.

SYSTEMS MONITORING

Definition: Tracking team resources and environmental conditions as they relate to mission accomplishment. This dimension includes internal systems monitoring and environmental monitoring.

Examples: - Tracking team related factors (e.g., political capital, constituent happiness, budget, time, rounds, or anything deemed relevant to the mission by the team) and ensure that these systems are operating effectively

Scale:

Complete Skill (5) – Team members effectively monitor factors related to political capital, budget, and happiness of constituents. Additionally, team members monitor other's individual task responsibilities and any communication generated within the team.

Very Much Skill (4)

Adequate Skill (3) - Team members, to a lesser degree monitor factors related to political capital, budget, and happiness of constituents. There may be some communication generated within the team, but they do not attend to it.

Some Skill (2)

Hardly Any Skill (1) – Team members have no idea how to monitor related to political capital, budget, and happiness of constituents, each other's individual task responsibilities, and any communication generated within the team.

TEAM MONITORING AND BACKUP BEHAVIOR

Definition: Assisting team members to perform their tasks. Assistance may occur by (a) providing a teammate verbal feedback or coaching, (b) by assisting a teammate behaviorally in carrying out actions, or (c) by assuming and completing a task for a teammate. This dimension includes the provision of feedback and task related support and the seeking of help from teammates when necessary.

Examples: - Keeping an eye on other teammates to determine if and when they need help
- Helping teammates with their assigned roles by telling them what to do and/or how to do it
- Team members inform each other of individual progress and setbacks
- Team members offer each other feedback
- Asking for or providing help in terms of how to perform certain tasks

Scale:

Complete Skill (5) – All team members monitor each other's specific roles and task requirements (e.g. ensuring that certain constituencies are monitored, asking the team to refer to their printed documents) to successfully complete the overall mission. Feedback and support are offered by team members and they are not afraid to ask for help if necessary.

Very Much Skill (4)

Adequate Skill (3) - Team members observe and are aware of each other's specific roles and task requirements (e.g. ensuring that certain constituencies are monitored, asking the team to refer to their printed documents). Feedback is offered by team members if necessary and they rarely ask for help.

Some Skill (2)

Hardly Any Skill (1) – Team members do not observe and are not aware of each other's specific roles and task requirements. Minimal feedback is offered by team members and they no team members ask for help when necessary.

COORDINATION

Definition: Orchestrating the sequence and timing of interdependent actions

Examples: - Organizing how and when team members will synchronize actions that require the contribution of all team members
- Organizing how and when team members will synchronize actions that require the efforts of more than one team member
- Sharing of information in order to establish who has what information about different constituents, policies, etc.

Scale:

Complete Skill (5) – Team members are in frequent contact with one another and maintain smooth coordination and synchronization of interdependent actions between individual roles and teams in accordance with the overall mission. Everyone's input is considered, and it is clear how the team arrives at their decisions.

Very Much Skill (4)

Adequate Skill (3) - Team members stay in contact with one another and maintain a minimum level of coordination and synchronization of interdependent actions between individual roles and teams in accordance with the overall mission. The input of team members is occasionally considered during coordination.

Some Skill (2)

Hardly Any Skill (1) – Complete lack of coordination and synchronization of interdependent actions between team members. The team is very disorganized, and no one knows what is going on. Decisions are made without the input of the team.

CONFLICT MANAGEMENT

Definition: Establishing conditions to prevent, control, or guide team conflict before it occurs. Working through task and interpersonal disagreements among team members.

Examples: - Making statements or offering opinions about task related issues, the way the team functions together, or personal issues, that are likely to affect subsequent team conflict.
- Attempting to work through disagreements when they arise within the team and are open to alternative ideas
- Rules are established in dealing with interpersonal conflict

Scale:

Complete Skill (5) – Team members openly discuss different approaches and strategies for the game without letting things get personal. All team members are considerate of differences and establish a pleasant and cooperative working environment. Team members are able to constructively discuss problems. If conflict does occur, team members are able to manage and contain the disagreements effectively.

Very Much Skill (4)

Adequate Skill (3) – Team members are willing to discuss different approaches and strategies for the game with relatively little ill feelings developing. Team members are sometimes considerate of differences and establish a fair working environment. Team members are able to discuss some problems and resolve most types of conflict. Some team members just “stay out” of any disagreements which may arise.

Some Skill (2)

Hardly Any Skill (1) – Team members are inconsiderate of differences; they establish an unpleasant and uncooperative working environment regarding the overall mission. Team members argue about problems in a destructive manner and often experience much conflict. They are completely unwilling to discuss the issue at hand and have no clue how to resolve the disagreement.

MOTIVATING AND CONFIDENCE BUILDING

Definition: Generating and preserving a sense of collective confidence, motivation, and task-based cohesion with regard to mission accomplishment.
Examples: - Members are motivated to work hard and do well
- Influencing the level of task cohesion of team members with respect to the goals of the task
- Team members have a shared sense that they can be successful

Scale:
Complete Skill (5) – All team members exhibit a strong sense of collective efficacy. This creates a positive attitude about the overall mission, and members seek to motivate one another through reinforcement and praise.
Very Much Skill (4)
Adequate Skill (3) – Team members exhibit a moderate sense of self efficacy and are motivated to do well. They believe that they can "hold their own" and do not fold in the face of adversity.
Some Skill (2)
Hardly Any Skill (1) – Collective efficacy is low in the team and people seem to be "going through the motions." When faced with adversity, the team members start to give up and believe that they cannot recover.

AFFECT MANAGEMENT

Definition: Regulating member emotions during mission accomplishment, including (but not limited to) social cohesion, frustration, and excitement.

Examples: - Influencing the positive and negative emotions of other members
- The members of the team are always ready to cooperate and help each other
- The members of the team stick together
- Relationships between members of the team are positive and rewarding

Scale:

Complete Skill (5) – While carrying out the mission objectives, team members effectively extinguished negative emotions and enhanced positive emotions. They were able to regulate and maintain a solid sense of emotional stability within the team.

Very Much Skill (4)

Adequate Skill (3) – While carrying out the mission objectives, team members extinguished their own negative emotions and retained some positive emotions. They were able to regulate and maintain a moderate level of emotional stability within their team.

Some Skill (2)

Hardly Any Skill (1) – While carrying out the mission objectives, team members failed to extinguish negative emotions and failed to enhance positive emotions. They were unable to regulate and maintain any sense of emotional stability within the team. If given the option, members would walk away from the entire experience.

Table 1. Total Count of Training and Testing Codes

Overall Model	# of Training Samples	# of Testing Samples	Total # of Samples
Total	4084	1022	5106

Table 2. Model Summary

Model	**Description**	**Data Used**	**Hypothesis**
Model 1	10-factor overall model	Engineering teams, NASA HERA teams, OR medical teams	*Hypothesis 1a-b; Hypothesis 3a-b*
Model 2	3-factor higher order model	Engineering teams, NASA HERA teams, OR medical teams	*Hypothesis 1a-b; Hypothesis 3a-b*
Model 3	Context Model	Engineering teams	*Hypothesis 2*
Model 4	Context Model	NASA HERA teams	*Hypothesis 2*
Model 5	Context Model	OR medical teams	*Hypothesis 2*
Model 6	BARS Rating Model	Engineering teams-Strategy Formulation Category	Exploratory
Human vs. Machine Coding	Human vs. Machine Coding	Engineering teams	*Hypothesis 4*

Table 3. 10-Factor Model Results

Class/Factor	# of Training Samples	# of Testing Samples	Total # of Text Samples	% Machine Accuracy
Mission analysis formulation and planning	238	63	301	17.46%
Goal specification	378	93	471	18.95%
Strategy formulation	686	172	858	52.05%
Monitoring Progress toward goals	240	58	298	5.00%
Systems monitoring	734	194	928	11.46%
Team monitoring and backup behavior	430	114	544	9.82%
Coordination	911	241	1152	25.42%
Conflict management	52	15	67	0.00%
Motivation and confidence building	114	31	145	6.90%
Affect management	136	41	177	10.53%

Note: The number of codes used in this model include: training = 3919, testing = 1022, total = 4941.

Table 4. 10-Factor Model Cross Classification Table

Class	Mission %	Goal %	Strategy %	Progress %	Systems %	Team %	Coordination %	Conflict %	Motivation %	Affect %
Mission	**17.46%**	28.58%	26.98%	0.00%	1.59%	3.17%	22.22%	0.00%	0.00%	0.00%
Goal	6.32%	**18.95%**	36.84%	3.16%	1.05%	4.21%	25.26%	0.00%	1.05%	3.16%
Strategy	9.23%	11.64%	**52.05%**	3.41%	2.24%	4.09%	16.17%	0.00%	1.17%	0.00%
Progress	0.00%	16.67%	38.33%	**5.00%**	6.66%	5.00%	26.67%	0.00%	0.00%	1.67%
Systems	3.13%	13.02%	27.08%	2.60%	**11.46%**	9.90%	31.77%	0.00%	0.00%	1.04%
Team	11.61%	10.71%	23.21%	1.79%	2.68%	**9.82%**	33.93%	1.79%	4.46%	0.00%
Coordination	16.25%	12.08%	28.33%	3.75%	2.08%	9.17%	**25.42%**	1.26%	0.83%	0.83%
Conflict	0.00%	13.33%	20.00%	6.67%	0.00%	6.67%	33.33%	**0.00%**	0.00%	20.00%
Motivation	0.00%	10.34%	6.90%	13.79%	0.00%	13.79%	44.83%	3.45%	**6.90%**	0.00%
Affect	0.00%	2.63%	0.00%	2.63%	7.89%	18.42%	52.63%	0.00%	5.27%	**10.53%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 5. 3-Factor Model Results

Class/Factor	**# of Training Samples**	**# of Testing Samples**	**Total # of Text Samples**	**% Machine Accuracy**
Transition	1299	328	1627	73.78%
Action	2309	607	2916	47.61%
Interpersonal	293	87	380	9.20%

Note: the number of codes used in this model include: training = 3901, testing = 1022, and total = 4923.

Table 6. 3-Factor Model Cross Classification Table

Class	Transition	Action	Process
Transition	**73.78%**	25.61%	0.61%
Action	51.90%	**47.61%**	0.49%
Process	26.44%	64.36%	**9.20%**

Table 7. Engineering Context Model Results

Class/Factor	# of Training Samples	# of Testing Samples	Total # of Text Samples	% Machine Accuracy
Mission analysis formulation and planning	144	42	186	23.81%
Goal specification	383	77	460	98.70%
Strategy formulation	540	136	676	51.47%
Monitoring Progress toward goals	87	23	110	0.00%
Systems monitoring	191	50	241	18.18%
Team monitoring and backup behavior	186	47	233	6.67%
Coordination	510	131	641	35.88%
Conflict management	30	8	38	14.28%
Motivation and confidence building	33	9	42	11.11%
Affect management	24	10	24	0.00%

Note: The number of codes used in this model include: training = 2128, testing = 533, and total = 2651.

Table 8. Engineering Context Model Cross Classification Table

Class	Mission %	Goal %	Strategy %	Progress %	Systems %	Team %	Coordination %	Conflict %	Motivation %	Affect %
Mission	**23.81%**	19.05%	11.90%	2.38%	2.38%	9.52%	23.81%	7.15%	0.00%	0.00%
Goal	0.00%	**98.70%**	0.00%	0.00%	0.00%	0.00%	1.30%	0.00%	0.00%	0.00%
Strategy	5.88%	13.97%	**51.47%**	11.03%	5.15%	2.21%	9.56%	0.73%	0.00%	0.00%
Progress	13.04%	13.04%	4.35%	**0.00%**	4.35%	0.00%	43.48%	17.39%	4.35%	0.00%
Systems	4.55%	13.64%	18.18%	22.73%	**27.27%**	4.55%	9.08%	0.00%	0.00%	0.00%
Team	15.56%	15.56%	20.00%	2.22%	2.22%	**6.67%**	26.67%	6.67%	4.43%	0.00%
Coordination	6.11%	21.37%	15.26%	1.53%	6.11%	9.16%	**35.88%**	3.05%	1.53%	0.00%
Conflict	0.00%	14.29%	14.29%	14.29%	14.29%	0.00%	28.55%	**14.29%**	0.00%	0.00%
Motivation	22.22%	11.11%	11.11%	0.00%	0.00%	11.11%	22.22%	11.11%	**11.11%**	0.00%
Affect	10.00%	40.00%	0.00%	0.00%	20.00%	0.00%	10.00%	10.00%	10.00%	**0.00%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 9. NASA Context Model Results

Class/Factor	# of Training Samples	# of Testing Samples	Total # of Text Samples	% Machine Accuracy
Mission analysis formulation and planning	70	17	87	0.00%
Goal specification	66	17	83	11.76%
Strategy formulation	119	31	150	19.35%
Monitoring Progress toward goals	125	32	157	21.88%
Systems monitoring	394	102	496	57.84%
Team monitoring and backup behavior	168	44	212	20.45%
Coordination	297	78	375	38.46%
Conflict management	22	6	28	16.67%
Motivation and confidence building	70	18	88	0.00%
Affect management	97	27	124	70.37%

Note: The number of codes used in this model include: training = 1428, testing = 372, and total = 1800.

Table 10. NASA Context Model Cross Classification Table

Class	Mission %	Goal %	Strategy %	Progress %	Systems %	Team %	Coordination %	Conflict %	Motivation %	Affect %
Mission	**0.00%**	5.88%	5.88%	0.00%	41.18%	23.53%	23.53%	0.00%	0.00%	0.00%
Goal	0.00%	**11.76%**	5.88%	5.88%	52.94%	11.76%	11.76%	0.00%	0.00%	0.00%
Strategy	0.00%	9.68%	**19.35%**	6.45%	32.26%	9.68%	19.35%	0.00%	3.23%	0.00%
Progress	0.00%	0.00%	0.00%	**21.88%**	53.13%	0.00%	21.88%	0.00%	3.13%	0.00%
Systems	0.00%	0.98%	0.98%	3.92%	**57.84%**	11.76%	23.53%	0.00%	0.98%	0.00%
Team	0.00%	0.00%	11.36%	11.36%	38.64%	**20.45%**	18.18%	0.00%	0.00%	0.00%
Coordination	0.00%	0.00%	5.13%	3.85%	37.18%	12.82%	**38.46%**	0.00%	1.28%	1.28%
Conflict	0.00%	0.00%	0.00%	16.67%	33.33%	0.00%	0.00%	**16.67%**	0.00%	33.33%
Motivation	0.00%	0.00%	0.00%	0.00%	0.00%	6.67%	13.33%	0.00%	**0.00%**	80.00%
Affect	0.00%	0.00%	0.00%	3.70%	11.11%	3.70%	11.11%	0.00%	0.00%	**70.37%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 11. OR Context Model Results

Class/Factor	# of Training Samples	# of Testing Samples	Total # of Text Samples	% Machine Accuracy
Mission analysis formulation and planning	17	5	22	0.00%
Goal specification	8	2	10	0.00%
Strategy formulation	28	7	35	0.00%
Monitoring Progress toward goals	28	7	35	0.00%
Systems monitoring	170	43	213	41.86%
Team monitoring and backup behavior	88	23	111	26.09%
Coordination	130	33	163	48.48%
Conflict management	0	0	0	0.00%
Motivation and confidence building	10	3	13	0.00%
Affect management	10	4	14	25.00%

Note: The number of codes used in this model include: training = 489, testing = 127, and total = 616.

Table 12. OR Context Model Cross Classification Table

Class	Mission %	Goal %	Strategy %	Progress %	Systems %	Team %	Coordination %	Conflict %	Motivation %	Affect %
Mission	**0.00%**	0.00%	0.00%	20.00%	40.00%	0.00%	40.00%	0.00%	0.00%	0.00%
Goal	0.00%	**0.00%**	0.00%	0.00%	0.00%	50.00%	50.00%	0.00%	0.00%	0.00%
Strategy	0.00%	14.29%	**0.00%**	0.00%	28.57%	0.00%	57.14%	0.00%	0.00%	0.00%
Progress	14.29%	0.00%	0.00%	**0.00%**	57.14%	0.00%	28.57%	0.00%	0.00%	0.00%
Systems	4.65%	0.00%	2.33%	13.95%	**41.86%**	25.58%	11.63%	0.00%	0.00%	0.00%
Team	4.35%	0.00%	13.04%	8.70%	30.43%	**26.09%**	17.39%	0.00%	0.00%	0.00%
Coordination	0.00%	12.12%	0.00%	0.00%	15.15%	24.24%	**48.48%**	0.00%	0.00%	0.00%
Conflict	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**0.00%**	0.00%	0.00%
Motivation	0.00%	0.00%	0.00%	0.00%	0.00%	66.67%	33.33%	0.00%	**0.00%**	0.00%
Affect	0.00%	0.00%	0.00%	0.00%	50.00%	0.00%	25.00%	0.00%	0.00%	**25.00%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 13. BARS Rating Model

Rating	# of Training Samples	# of Testing Samples	Total # of Text Samples	% Machine Accuracy
1-Hardly Any Skill	28	7	35	28.57%
2-Some Skill	30	7	37	14.29%
3-Adequate Skill	50	13	63	46.15%
4-Very Much Skill	16	4	20	0.00%
5-Complete Skill	14	4	18	25.00%

Note: The number of codes used in this model include: training = 138, testing = 35, and total = 173.

Table 14. BARS Rating Model Cross Classification Table

Class	1 Hardly Any Skill %	2 Some Skill %	3 Adequate Skill %	4 Very Much Skill %	5 Complete Skill %
1 Hardly Any Skill	**28.57%**	14.29%	42.86%	0.00%	14.29%
2 Some Skill	28.57%	**14.29%**	57.14%	0.00%	0.00%
3 Adequate Skill	23.08%	15.38%	**46.15%**	0.00%	15.38%
4 Very Much Skill	0.00%	50.00%	50.00%	**0.00%**	0.00%
5 Complete Skill	0.00%	25.00%	25.00%	25.00%	**25.00%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 15. Human vs. Machine Coding Model Results

Class/Factor	# of Testing Samples	% Machine Accuracy	% Human Accuracy
Mission analysis formulation and planning	2	0.00%	50.00%
Goal specification	20	31.58%	36.84%
Strategy formulation	39	31.58%	50.00%
Monitoring Progress toward goals	13	0.00%	7.69%
Systems monitoring	52	31.37%	62.75%
Team monitoring and backup behavior	20	10.00%	50.00%
Coordination	347	17.92%	16.47%
Conflict management	2	100.00%	100.00%
Motivation and confidence building	21	28.57%	52.38%
Affect management	6	33.33%	50.00%

Note: The total number of codes used in this model is 522.

Table 16. Machine Coding Cross Classification Table

Class	Mission %	Goal %	Strategy %	Progress %	Systems %	Team %	Coordination %	Conflict %	Motivation %	Affect %
Mission	**0.00%**	50%	50%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Goal	0.00%	**31.58%**	42.11%	5.26%	0.00%	0.00%	21.05%	0.00%	0.00%	0.00%
Strategy	10.53%	28.95%	**31.58%**	0.00%	0.00%	2.63%	23.68%	0.00%	0.00%	2.63%
Progress	23.08%	23.08%	23.08%	**0.00%**	0.00%	0.00%	30.77%	0.00%	0.00%	0.00%
Systems	1.96%	5.88%	17.65%	0.00%	**31.37%**	11.76%	29.41%	0.00%	0.00%	1.96%
Team	0.00%	15.00%	10.00%	0.00%	5.00%	**10.00%**	55.00%	5.00%	0.00%	0.00%
Coordination	6.36%	17.34%	47.40%	2.60%	5.78%	2.31%	**17.92%**	0.29%	0.00%	0.00%
Conflict	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**100%**	0.00%	0.00%
Motivation	0.00%	14.29%	9.52%	0.00%	0.00%	0.00%	0.00%	14.29%	**28.57%**	33.33%
Affect	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	66.67%	**33.33%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 17. Human Coding Cross Classification Table

Class	Mission %	Goal %	Strategy %	Progress %	Systems %	Team %	Coordination %	Conflict %	Motivation %	Affect %
Mission	**50.00%**	50.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Goal	0.00%	**36.84%**	15.79%	5.26%	10.53%	0.00%	15.79%	5.26%	10.53%	0.00%
Strategy	15.79%	18.42%	**50%**	0.00%	0.00%	0.00%	10.53%	0.00%	0.00%	5.26%
Progress	15.38%	0.00%	23.08%	**7.69%**	23.08%	0.00%	0.00%	0.00%	0.00%	0.00%
Systems	3.92%	3.92%	27.45%	0.00%	**62.75%**	0.00%	0.00%	0.00%	0.00%	1.96%
Team	0.00%	5.00%	10.00%	0.00%	0.00%	**50%**	35.00%	0.00%	0.00%	0.00%
Coordination	4.62%	14.45%	33.82%	3.76%	20.52%	5.78%	**16.47%**	0.58%	0.00%	0.00%
Conflict	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**100%**	0.00%	0.00%
Motivation	0.00%	19.05%	0.00%	0.00%	0.00%	0.00%	0.00%	4.76%	**52.38%**	23.81%
Affect	0.00%	0.00%	0.00%	0.00%	0.00%	16.67%	0.00%	0.00%	33.33%	**50.00%**

Note: Column 1 displays the class being analyzed, while the row headers show the percentage of agreement between machine and human codes.

Table 18. Example Text Summary Table

Team Process	Example Text
Mission Analysis	Do we want to start on some type of functional model?
Mission Analysis	Let's come up with just a generalized problem statement or do we have a generalized problem statement?
Mission Analysis	Let's just say that would be a requirement, so let's not put that in the problem statement. I mean, a constraint. I don't know if we need to add anything to the actual problem statement, honestly.
Goal Specification	Yeah. I think our goal should be, for this meeting, to get a rough functional model and we'll update constraints and criteria as well.
Goal Specification	Yeah I understand I think just for today the goal was to get us to sign everything off within decent parameters.
Goal Specification	Our goal is to get some values in the signoff sheet this time since we ran out of time last time
Strategy Formulation	Hopefully, we can just assign, just touch base on what this needs to be now, and then assign stuff to do. And then we're going to need to decide on what type of functional model to do. We're talking about doing a function tree and some type of model or whatever.
Strategy Formulation	Yeah, after we get the functional model, we'll do a whole layout of the measurements we took to see what's going to be
Strategy Formulation	No. I feel like we've already done these first few things in the problem definition stuff and we were into the conceptual design, we just didn't really document it and they didn't really understand that. I think we just need to document some of these, like our PDS. We'll do, like I was saying, a function tree.
Monitoring Progress	Let’s get this patient out of here but the fire’s under control.
Monitoring Progress	There are no concerns to report at this time.
Monitoring Progress	It's problem and background, we've been doing this wrong
Systems Monitoring	Yeah, I don't know, it says my username won't even work.
Systems Monitoring	No, I can't edit it. I don't like editing it on the online thing. I won't let me edit it in Excel.
Systems Monitoring	Do you guys know how to start a PowerPoint presentation with the Microsoft PowerPoint?
Team Monitoring	What you can do is, you can open the one that I'm sending to you, and just copy the heading of the PDS for what we did.
Team Monitoring	I feel like Chris has a good understanding about what the sensitivity does. QFD sounds really good but it sounds so complicated, he can show us.

Team Monitoring	Waiting on Drilling Specialist (HERA Crew) to determine drilling method so we can update materials and operations parameters. Will update you when we can.
Coordination	I have a shared document that I'm about to send everybody.
Coordination	What are you thinking to lifts? Are you wanting to press a button with hydraulics?
Coordination	Sharing that info with other teams and will update on our numbers shortly.
Conflict Management	I'm sorry. I ignored you.
Conflict Management	Sorry it took me so long to respond I had a billion messages.
Conflict Management	I'm sorry to badger you guys about it
Motivation/Confidence Building	That's a good idea.
Motivation/Confidence Building	Great job by everybody
Motivation/Confidence Building	Let's do this!
Affect Management	You guys are the best.
Affect Management	Thank you I appreciate you.
Affect Management	Hi again and welcome to another great session.

Figure 1

Team Process Framework and Definitions (Marks et al., 2001)

TABLE 1
Taxonomy of Team Processes

Process Dimensions	Definition	Previous Research on Team Processes
Transition processes		
Mission analysis formulation and planning	Interpretation and evaluation of the team's mission, including identification of its main tasks as well as the operative environmental conditions and team resources available for mission execution	Fleishman & Zaccaro (1992); Prince & Salas (1993)
Goal specification	Identification and prioritization of goals and subgoals for mission accomplishment	Dickinson & McIntyre (1997); Levine & Moreland (1990); O'Leary-Kelly, Martocchio, & Frink (1994); Prussia & Kinicki (1996); Saavedra, Early, & van dyne (1993)
Strategy formulation	Development of alternative courses of action for mission accomplishment	Cannon-Bowers, Tannenbaum, Salas, & Volpe (1995); Gladstein (1984); Hackman (1983); Hackman & Oldham (1980); Prince & Salas (1993); Stout, Cannon-Bowers, Salas, & Milanovich (1999); Weldon, Jehn, & Pradhan (1991)
Action processes		
Monitoring progress toward goals	Tracking task and progress toward mission accomplishment, interpreting system information in terms of what needs to be accomplished for goal attainment, and transmitting progress to team members	Cannon-Bowers, Tannenbaum, Salas, & Volpe (1995); Jentsch, Barnett, Bowers, & Salas (1999)
Systems monitoring	Tracking team resources and environmental conditions as they relate to mission accomplishment, which involves (1) internal systems monitoring (tracking team resources such as personnel, equipment, and other information that is generated or contained within the team), and (2) environmental monitoring (tracking the environmental conditions relevant to the team)	Fleishman & Zaccaro (1992)
Team monitoring and backup behavior	Assisting team members to perform their tasks. Assistance may occur by (1) providing a teammate verbal feedback or coaching, (2) helping a teammate behaviorally in carrying out actions, or (3) assuming and completing a task for a teammate	Dickinson & McIntyre (1997)
Coordination	Orchestrating the sequence and timing of interdependent actions	Brannick, Prince, Prince, & Salas (1992); Brannick, Roach, & Salas (1993); Fleishman & Zaccaro (1992); Zalesny, Salas, & Prince (1995)
Interpersonal processes		
Conflict management	Preemptive conflict management involves establishing conditions to prevent, control, or guide team conflict before it occurs. Reactive conflict management involves working through task and interpersonal disagreements among team members	Cannon-Bowers, Tannenbaum, Salas, & Volpe (1995); Gladstein (1984); Jehn (1995); Pace (1990); Simons, Pellad, & Smith (1999); Simons & Peterson (2000); Smolek, Hoffman, & Moran (1999); Tjosvold (1985); Van de Vliert, Euwema, & Huismans (1995)
Motivation and confidence building	Generating and preserving a sense of collective confidence, motivation, and task-based cohesion with regard to mission accomplishment	Fleishman & Zaccaro (1992)
Affect management	Regulating member emotions during mission accomplishment, including (but not limited to) social cohesion, frustration, and excitement	Cannon-Bowers, Tannenbaum, Salas, & Volpe (1995)