Unobtrusive Measures and Understanding Team Processes

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ABSTRACT

The need to examine team processes with more innovative approaches is well-documented, as much of the literature has utilized self-report or subjective measures which are often biased, intrusive, and/or provide a static, retrospective evaluation (Kozlowski & Chao, 2018). Further, in the military, it is often impossible or unrealistic to have trained observers in dangerous or classified environments, or for warfighters to stop their tasks to take a survey. Recent advancements in technology (e.g., wearable sensors), coupled with the issues related to subjective data, have created new opportunities for researchers to examine team processes using less invasive or obtrusive approaches (Orvis et al., 2013). While such advancements in technology are promising for the development of unobtrusive and objectives measures, there are also well-documented concerns regarding the lack of rigor in the development of unobtrusive measures as they often lack conceptual or theoretical backing (Salas et al., 2015). As a result, the following paper takes a comparative look at an unobtrusive measure developed using a rigorous framework, the Rational Approach to Developing Systems-based Measures (RADSM; Orvis et al., 2013), with subjective measures from observers and survey assessments. The following paper utilizes data from a large-scale, military-inspired experimental research study with a variety of unobtrusive data (i.e., audio data, video data, and positional data) and subjective data (i.e., observations, survey measures) collected from five-person teams completing a military-like exercise. We present best practices for measure development and validation as well as insights regarding the strengths and limitations of both unobtrusive and subjective measures so that readers can better understand the different methodologies of capturing team processes and the implications of both within their own work.

ABOUT THE AUTHORS

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Dr. Robert McCormack is a Principal Research Engineer and Director of the Intelligent Performance Analytics Division, Aptima, Inc. He has spent over 15 years working with scientists and engineers to develop and deliver data-driven solutions for understanding and predicting individual and team performance dynamics. With expertise in artificial intelligence, machine learning, and statistical methods, he has extensive experience analyzing both structured and unstructured data to extract meaningful information. Dr. McCormack received a PhD and MS in mathematics from Texas Tech University, and a BA in mathematics and computer science from Austin College.

Dr. Kara Orvis, Executive Vice President of the Research and Development (R&D) Group at Aptima. She is also a Principal Scientist with 20+ years of experience in Government R&D with the Army, Air Force, and Marine Corps.

Her expertise in the areas of training, leadership, teams, culture, distributed work, and unobtrusive measurement has resulted in 70+ publications/presentations, including one edited book. Dr. Orvis holds a PhD and MA in Industrial-Organizational Psychology from George Mason University, and a BA in Psychology from Ohio Wesleyan University. She is a member of the American Psychological Association and the Society for Industrial and Organizational Psychology.

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Dr. Dorothy Cater is an Associate Professor at Michigan State University and directs the Leadership, Innovation, Networks, and Collaboration (LINC) Laboratory. The LINC Lab aims to better understand phenomena that enable leaders, teams, and larger systems to tackle complex challenges in organizational contexts including the military, medicine, scientific research, corporations, and deep-space exploration. Dr. Carter's research advances a view of team leadership as a dynamic and networked relational process that emerges and evolves among team members who may or may not occupy formal positions of authority. Her research program has been supported by funding from the National Science Foundation (NSF), The Army Research Institute (ARI), the National Institutes of Health (NIH), and the National Aeronautics and Space Administration (NASA).

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Dr. Eduardo Salas is the Allyn R. & Gladys M. Cline Chair Professor in Department of Psychological Sciences at Rice University. His expertise includes assisting organizations, including oil and gas, aviation, law enforcement and healthcare industries, in how to foster teamwork, design and implement team training strategies, how to create a safety culture and minimize errors, facilitate learning and training effectiveness, optimize simulation-based training, manage decision making under stress, and develop performance measurement tools. Dr. Salas has co-authored over 650 journal articles & book chapters and has co-edited 37 books and handbooks, authored one book on team training and has one on teamwork. His work has been cited over 125,000 times. He is a Past President of the Society for Industrial/Organizational Psychology (SIOP) and the Human Factors & Ergonomics Society (HFES). He is a Fellow of the American Psychological Association (APA), Association for Psychological Science and HFES. He is also the recipient of the 2012 Society for Human Resource Management Losey Lifetime Achievement Award, the 2012 Joseph E. McGrath Award for Lifetime Achievement from the Interdisciplinary Network of Group Research for his work on teams and team training and the 2016 APA Award for Outstanding Lifetime Contributions to Psychology.

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INTRODUCTION

Given the well-established importance of teams within organizations, ample research has explored and documented different team-related constructs and processes (Kolbe & Boos, 2019; Kozlowski, 2015; Salas et al., 2015a). Despite the robust literature examining such processes (e.g., team cohesion, coordination), research has also highlighted the need to better understand and capture team processes with more innovative (Kozlowski, 2015; Kozlowski & Chao, 2018), robust (Salas et al., 2008), and specific (Espinosa et al., 2004) approaches. Previously, much of the research examining teams utilized subjective measures or assessments, which often include individual perceptions or behavioral observations and can therefore be limited because of bias, fatigue, and time constraints (Feese et al., 2014; Kolbe & Boos, 2019; Orvis et al., 2013; Orvis et al., 2016). Recent advancements in technology, coupled with the issues related to subjective measures, have created new opportunities to examine team processes using less invasive or obtrusive approaches, such as wearable devices and sensors. Such devices offer several advantages when compared to subjective assessments such as the ability to collect data continuously as well as through a variety of data sources (e.g., email, GPS, sensors; Khaleghzadegan et al., 2020; Orvis et al., 2016).

Technological advances and increasingly complex workplaces present an opportunity for organizations, such as the military, to collect large amounts of data to better understand organizational outcomes (Khaleghzadegan et al., 2020; Orvis et al., 2013). For example, aspects of the military (e.g., training, operations, deployments, etc.) are becoming more reliant on a collaborative infrastructure that is dispersed, such that individuals, teams, and leadership are more frequently communicating while temporally and spatially distributed (Salas et al., 2008). As technology continues to support these distributed organizations of teams, the complexity of communication and collaboration also increases. The result is a highly intertwined workforce with opportunities for unobtrusive data collection, to include data from cell phones, wearables, email, and different chat systems (e.g., Slack; Orvis et al., 2013).

Unobtrusive measures are defined as measurements that can be collected without utilizing subjective assessments of individuals (e.g., observer-rated, self-rated) and are usually less intrusive in nature (e.g., wearable sensors such as an Apple watch; Khaleghzadegan et al., 2020; Kozlowski et al., 2015; Webb et al., 1966). While there are several benefits to unobtrusive technologies and the subsequent amount of data they provide access to, previous research has also highlighted some of the challenges that come with big data, including how to manage and interpret large amounts of organizational data, as well as the challenges of relying solely on data-driven approaches (Orvis et al., 2013; Salas et al., 2015a). Although data-driven approaches are certainly important, previous research has noted the potential issues with utilizing an approach that fails to consider theory or subject matter expertise (Graham, 2012; Orvis et al., 2013). Further, while unobtrusive measures are often implemented to capture established psychological constructs, they often fail to adequately capture the construct of interest due to a lack of sufficient development of the specific unobtrusive indicator (Grijalva et al., 2020; Salas et al., 2015a).

As a result of these concerns, Orvis and colleagues (2013) developed the Rational Approach to Developing Systems-based Measures (RADSM) process as a way to integrate both theory and unobtrusive data when creating measures using unobtrusive data sources. The RADSM process offers a six-step systematic approach and considers both available unobtrusive data (bottom-up) and theory (top-down) to map measures derived from unobtrusive data on to previously established psychological constructs (e.g., coordination). Given the potential advantages of the RADSM approach, the current study examined the efficacy of the RADSM process in developing and validating an unobtrusive measures of team coordination during a military-like exercise. Further, the current study extended previous research by examining the efficacy of the developed measure in predicting team performance when compared to a more traditional assessment, a survey assessment of team coordination. Team coordination was selected given the importance of coordination in high-stress and high-reliability organizations, such as the military, as well as previous work that has empirically and theoretically demonstrated the need for team coordination to improve performance outcomes (Braun et al., 2020; Gode & Lebraty, 2015; Salas et al., 2008).

Unobtrusive Measures

As technological capabilities improve, organizations will have increased access to different methods of data collection, many of which offer more unobtrusive methods to capture human behavior (e.g., email communication, GPS, wearable devices, etc.; Hill et al., 2014; Khaleghzadegan et al., 2020; Orvis et al., 2016). Unobtrusive measures have several advantages when compared with subjective measures, including minimizing bias and the subjectivity of self-rated or observer-rated assessments (Auriacombe, 2016; Orvis et al., 2016). Unobtrusive measures also allow for multiple approaches to collect a variety of data of the same psychological construct and can also be less costly and labor intensive, which can increase the amount of data collected (Hill et al., 2014). In addition, unobtrusive measures can be collected without distracting or disrupting workflow, unlike subjective assessments, which often require introducing a trained observer within the workplace environment or stopping work to complete an assessment (Auriacombe, 2016; Baek & Ihm, 2021; Hill et al., 2014; Orvis et al., 2016). Utilizing subjective measures also requires active participation by a willing participant, which can often be difficult to obtain, especially for employees or operators in fast-paced environments such as in the military (e.g., combat; Hill et al., 2014; Webb et al.,1966).

Within the military, unobtrusive data can be valuable to better understanding performance outcomes and mission readiness, to include chat data from a distributed exercise to sensor data during a deployment mission (Orvis et al., 2013). Further, certain features of the military such as size, the importance of safety, and the overall increased risk make utilizing unobtrusive measurements that do not require a trained observer and do not interrupt or impact workflow especially desirable (Orvis et al., 2016; Salas et al., 2015a). For example, it may be impossible or unrealistic to have a trained observer in certain environments or for warfighters to stop their tasks to take a survey (Salas et al., 2015a). Previous research in military environments have utilized unobtrusive data methods, such as wearables, to increase access to physical and cognitive states. For example, Heaton and colleagues (2020) demonstrated the use of speech-motor coordination and electrodermal activity (EDA) to predict cognitive fatigue in service members. Specifically, certain vocal features (e.g., vocal quality) extracted from audio recordings were able to significantly predict cognitive performance. Further, EDA sensors, which measure changes in skin conductance, were able to demonstrate a relationship between increased arousal and cognitive performance. Both audio recordings and EDA sensors are valuable in that they provide unobtrusive mechanisms to capture physiological and behavioral signals (e.g., speech; Heaton et al., 2020).

While there are several advantages of unobtrusive measures, as previously discussed, there are also shortcomings (Auriacombe, 2016). For example, as a result of certain complexities associated with unobtrusive measures (e.g., construct development, large amounts of data, significant storage resources), unobtrusive measures are often poorly implemented in a way that fails to fully utilize their advantages (Hill et al., 2014; Khaleghzadegan et al., 2020). Further, previous research has noted concerns with the reliability and validity of unobtrusive measures (Hill et al., 2014; Khaleghzadegan et al.,2020; Salas et al., 2015a). Hill and colleagues (2014) identified two primary concerns as it relates to the use of unobtrusive measures. The first concern is that there often lacks a theoretical rationale connecting the unobtrusive measure to the construct of interest. The second concern is that there often lacks a rigorous process examining alternative explanations for outcomes. Therefore, more attention should be given to the validation process of unobtrusive measures in order to demonstrated construct validity. As a result, while unobtrusive measures can be utilized on their own, previous research has demonstrated that there are advantages to combining unobtrusive measures with complementary methods such as survey data (Auriacombe, 2016; Hill et al., 2014). This is especially relevant during early stages of unobtrusive measurement in order to better establish construct validity (Grijalva et al., 2020; Salas et al., 2015a).

The RADSM Process

As previously mentioned, a benefit of unobtrusive measures is their ability to provide more robust and varied types of data that describe a singular psychological construct (Hill et al., 2014). However, this can complicate interpreting the data, as most psychological constructs have been defined and validated in the context of subjective measures. As a result, the six-step RADSM process was developed by Orvis and colleagues (2013) in order to integrate big data methodologies with theory-based science to better examine different constructs and draw conclusions within systems. The RADSM process is heavily reliant on the use of objective measurement that captures human behavior, also known as biodata (Orvis et al., 2013). As a result, the RADSM process draws on other approaches that capture biodata. The RADSM process, however, builds upon previous techniques by specifically outlining iterative steps using data availability, theory, and multi-disciplinary data analytic methods to develop constructs (Orvis et al., 2013). Further, the RADSM process is more flexible and extensive in that it can utilize multiple sources of data, including unobtrusive measurements (Orvis et al., 2013).

The RADSM process includes six steps that are designed to approach the development of constructs from both a bottom-up and top-down methodology (see Figure 1 for an overview of the process). The first step of the process is to identify the construct of interest, to include considering the full extent of the construct of interest (e.g., conceptual basis of the construct), as well as thinking through any contextual implications of the construct in the desired environment (Orvis et al., 2013). The next step is to generate a list of construct indicators, which are described as attributes and behaviors that are related to the construct of interest. Such construct indicators are often observable characteristics of a construct. As a result, this step is heavily reliant on utilizing previous research and SME input. The third step includes the explicit analysis of methodologies specific to systems (e.g., network analysis, methods of communication, etc.; Orvis et al., 2013) within the environment of interest. Within the RADSM process, this step serves as an opportunity to consider any and all possible systems-based approaches that could be used. The next step in the RADSM process is to link the theoretical and empirical indicators identified in step two with the possible sources of systems-based data in step three. Each available source is then created into an item, similar to an item within a survey. The compiled list of items is then used to describe the construct of interest. Because each item is linked to a construct indicator, the result of this step is a systems-based measure of available information in which each item is rooted in theory and expertise. The fifth step in the RADSM process is to examine the data, which also included examining the data to ensure the data are collected and properly managed (Orvis et al., 2013). Lastly, the final step within the RADSM process is to validate the systems-based measure of the construct of interest. Like other processes that develop measures, this step includes examining different forms of validity such as evidence of construct validity, to include face validity as well as convergent and discriminant validity (Orvis et al., 2013).

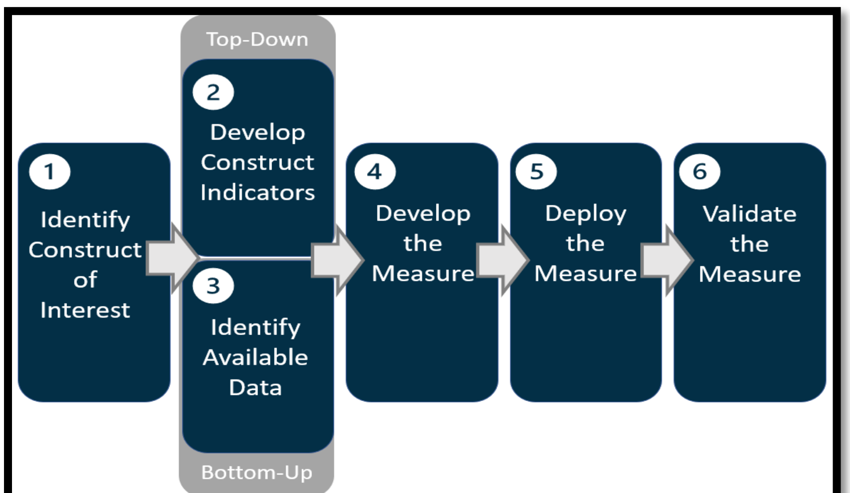

Figure 1. The RADSM Process

Unlike subjective measures that are consistent between different samples, measures derived using the RADSM process may deviate from previous research due to differences in the availability of certain measures. In other words, it is unlikely that a measure of coordination created using the RADSM process would be the exact same measure of coordination in a differing sample unless the two approaches utilized identical unobtrusive data sources and extracted the same items from such sources. As a result, the RADSM process should be continuously validated as new forms of unobtrusive data sources are captured. Previously, the RADSM process has been validated in examining systems-based shared situational awareness (SSA) and has been used in other research efforts to capture systems-based measures such as coordination (Orvis et al., 2013; McCormack et al., 2017).

Team Processes and Coordination

Team processes are defined as "members' interdependent acts that convert inputs to outcomes through cognitive, verbal and behavioral activities directed toward organizing taskwork to achieve collective goals" (Marks et al., 2001, pg. 357) and often encompass activities a team needs to perform that facilitate success. As a result, team processes are often linked to performance and include examples such as information sharing and coordination (Feese et al., 2014; Mathieu et al., 2000). The link between team performance and teamwork as a process has drastically impacted the ways in which teams are studied (Marks et al., 2001). As a result, understanding how team members work together to form an integrated approach to task performance is important to understanding team success (Gabelica et al., 2016; Nawata et al., 2020). Further, identifying specific team processes, such as coordination, that can be selected for, bolstered in training, and developed may be especially relevant to improving team performance (Marks et al., 2001).

As the size, complexity, and interdependence of teams continue to increase, certain processes such as team coordination become especially important (Espinosa et al., 2004). Coordination is an important feature of teamwork and is described as a process in which both observable behaviors (e.g., information sharing) and shared adjustments and task planning (e.g., the distribution of tasks with the team) occur (Burtsher et al., 2011). Simply put, coordination can be described as the management of interdependent activities for a shared purpose within a team of two or more people (Gode & Lebraty, 2015; Malone & Crowston, 1994; Salas et al., 1992). Team coordination has been a focus of researchers since the beginning of the last century, likely due to ample empirical evidence that it influences several important organizational outcomes such as performance (Chang et al., 2017; Espinosa et al., 2004). In addition to being examined as a unidimensional construct, team coordination is often examined as a multidimensional construct and often includes both explicit (teams operating through plans, procedures, and schedules, as well as different forms of communication) and implicit coordination (teams operating through shared cognition; Espinosa et al., 2004; Kolbe et al., 2011).

The military in particular presents as a unique organizational environment where team coordination can be crucial. To begin, the military is largely made up of a network of teams, often varying in size (e.g., squad, platoon, etc.), making effective teamwork important for success (Giachetti & Rojas, 2007). In addition, such teams are often distributed and operate in complex and dangerous scenarios, further exacerbating the need for coordinated efforts (Giashetti & Rojas, 2007; Shah & Breazeal, 2010; Yammarino et al., 2010). Taken together, the structure of the military, paired with the potential complexity of both military tasks and operational environments, requires a high level of team coordination for success. As a result of the clear need for coordination in military teams, military researchers, along with other disciplines, have highlighted the importance of team coordination for mission success (Chang et al., 2017). Specifically, several research efforts have demonstrated the impact of team coordination on different outcomes such as stress, performance, and increased errors (Entin & Serfaty, 1999; Serfaty et al., 1998; Wilson et al., 2007).

As technology advances and expands within organizations, to include the military, understanding how such advancements can be utilized to better understand team processes is especially important (Carmody et al., 2017). Wearables offer a wide variety of mechanisms to examine team processes (Salas et al., 2015b), including physiological data like heart rate variability (HRV), voice data (e.g., vocal duration, speech patterns, pitch, tempo), movement data, position data (e.g., posture), and data from face-to-face interactions (Khaleghzadegan et al., 2020; Salas et al., 2015b). For example, communication pattern analyses can be conducted on recorded vocal data to examine different patterns in team interactions (e.g., vocal intensity; Salas et al., 2015b). Paired together, wearable sensor suites can provide a variety of inputs that, through the use of algorithms, can highlight anomalies within team interactions and can be used for targeted interventions in order to improve team processes, such as coordination (Kozlowksi et al., 2018; Salas et al., 2015b).

HYPOTHESES AND METHOD

The hypotheses for the current study address (1) the validation of the measure of team coordination developed using unobtrusive data and (2) the extension of those findings by examining the relationship between team coordination and performance using both a subjective measure as well as the developed unobtrusive measure. First, it is hypothesized that the developed unobtrusive measure of team coordination will be related to an identical construct (coordination) as well as a similar construct (Transactive Memory System [TMS] expertise coordination), therefore demonstrating convergent validity (Hypothesis 1 [H1]; Westen & Rosenthal, 2003). Second, it is hypothesized that the developed unobtrusive measure of team coordination will not be related to a dissimilar construct (psychological safety), therefore demonstrating discriminant validity (Hypothesis 2 [H2] Westen & Rosenthal, 2003).

Next, similar to previous research that has empirically linked coordination and performance (e.g., Bowers & Salas, 1998; Butchibabu, 2016; Entin & Serfaty, 1999), it is hypothesized that both a subjective measure of team coordination as well as the developed measure of unobtrusive team coordination will individually predict performance (Hypothesis 3 [H3]). In addition, it is hypothesized that when within the same model, the developed unobtrusive measure of team coordination will predict performance above and beyond the subjective measure (Hypothesis 4 [H4]). Although more exploratory in nature, this hypothesis examines cross-data source differences in predicting performance. More explicitly, it could be that the two measures collected from different data sources (e.g., subjective vs. unobtrusive) relate to and predict performance differently.

Participants

Participants include 95 individuals (civilians) comprising 38, 5-person teams completing a military-like exercise. Data were collected at four different universities. Given the use of university recruitment processes, 95.8% of the sample was 25 or younger (M= 20.38, SD= 3.68). However, participation was not limited to university students and therefore included non-university adults 18-years or older. 53.7% of the sample was female, 40.7% of the sample was male, 3.2% of the sample was non-binary or preferred not to self-describe. In addition, 80% of the sample was white, 15.9% of the sample was non-white, and 5.3% of the sample preferred not to specify.

Team Tasks

The military-like exercise was completed within an experimental research paradigm and was designed to mirror tasks performed by small military teams. Although the tasks varied across the missions, all three missions were intentionally designed to mirror each other and have comment elements, to include navigating the field, solving puzzles, and building objects. As part of the exercise, each team had to complete three individual missions, to include a Humanitarian Aid Mission, a Search and Retrieve Mission, and an Escape Mission. Within the experimental research design, each team first completed the Humanitarian Aid mission. Following the Humanitarian Aid Mission, the order of the following two missions (Search and Retrieve Mission and Escape Mission) were counterbalanced. The Humanitarian Aid Mission was not counterbalanced in order to provide baseline mission performance across all sessions. For the purpose of the current study, data from the Humanitarian Aid Mission was excluded as the first mission demonstrated an increased learning curve as participants familiarized themselves with their team members and the experimental paradigm as a whole.

Within each exercise, participants were randomly assigned to a role within each five-person team. Team roles include a leader, navigator, security officer, intelligence officer, and engineer. Each role was created in order to reflect key roles or responsibilities within military teams. In addition to completing the objectives for each mission, the teams had to accurately navigate the field using military formations while also avoiding enemy detection and collecting bonus supplies.

Data and Measures

The current study utilized self-report survey data (collected using smartphone devices), observational data (collected using tablets), and continuous unobtrusive audio data (collected using Bluetooth earpieces connected to smartphones). Self-report survey data was collected prior to participation in the exercise (pre-survey), before each of the three missions (e.g., pre-mission), after each of the three missions (e.g., post-mission), as well as following the conclusion of the exercise (post-survey). Measures for the current study included subjective, self-report measures of team coordination (Mathieu et al., 2020), TMS expertise coordination (Faraj & Sproull, 2000), and psychological safety (Edmondson, 1999). A study-specific measure of team performance was developed in which trained observers rated team performance on a scale of 1-5 post-mission (ICC=.822).

Lastly, a measure of team coordination was developed using the RADSM process. The unobtrusive measure of team coordination consisted of ten items that mapped on to aspects of team coordination. Five of the items represented team averages for indicators of coordination, including: Team communication (average number of words spoken), Team questions (average number of questions spoken), Team acknowledgements (average number of acknowledgements [e.g., "Got it," "Okay," "Rodger"] spoken), Team role-information shared (average number of role-specific keywords shared), and Team keywords (average number of keywords spoken). In addition, five of the items represented team communication dispersion. The team communication dispersion items were calculated using the standard deviation value and were utilized to demonstrate the dispersion of coordination across the team, including: Team communication dispersion, Team questions dispersion, Team acknowledgements dispersion, Team role-specific information dispersion, and Team keywords dispersion. Within the current study, the items were examined both individually as well as examined using the factor structure of the developed measure.

Subjective team coordination, TMS expertise coordination, and psychological safety were analyzed using an average score on each measure such that increased scored indicated increased levels of each construct. Audio data for each indicator was processed using Otter AI. More explicitly, audio transcripts for each of the five roles were stitched together to form one aggregate audio file. The aggregate file was then uploaded and transcribed by Otter AI, which is a text-transcription software that utilizes Artificial Intelligence (AI) to for both audio transcription and speaker differentiation. Although previous research has utilized AI-based transcription software such as OtterAI (Cobbina, 201), issues with the quality of the audio files required a majority (> 95%) of the audio transcript to be transcribed within Otter AI by hand. The end result was one transcription with representation from all five roles.

Once the audio files were transcribed, dialogue analyses were conducted to develop each of the ten indicators. For the indicators that utilized total counts (Team communication and Team questions), totals were created through words counts within the transcription files. For the indicators that utilized word lists (Team role-specific information, Team keywords, and Team acknowledgments), lists of key words or phrases were generated and used to extract the total number of the identified words. For indicators that utilized dispersions (Team communication dispersion, Team role-specific information shared dispersion, Team keywords dispersion, Team acknowledgements dispersion, and Team questions dispersion), dispersions were calculated by calculating the standard deviation. Dialogue analyses were conducted using a developed python script run on Jupyter notebook (Kluyver et al., 2016). More specifically, transcripts for each team member and for each mission were uploaded to Jupyter notebook as .txt files. Using a python script, the output of the dialogue analyses was produced in an Excel file.

RESULTS

The current study conducted a Principal Component Analyses (PCA), Exploratory Factor Analysis (EFA), and a Confirmatory Factor Analysis (CFA) as part of the measure development and validation process of the unobtrusive measure of team coordination. Both a Bartlett's Test of Sphericity and a Kasier-Meyer-Olkin (KMO) test demonstrated that the data were well-suited for factor analysis (p <.05; MSA=.71, respectively). A PCA revealed 4 underlying components which were used to examine a 4-factor model. The model had adequate fit with an improved fit when covariances were added. The end result was a 9-item, 4 factor measure of unobtrusive team coordination. Although guidance suggests that factors should have at least three items (Costello & Osborne, 2005) the use of a 4-factor structure was utilized due to conceptual reasons. Further, existing measures have utilized two-item factor structures (Rammstedt & John, 2007). See Figure 2 for a summary of the results for H1-H4.

H1 posited that the developed measure would demonstrate convergent validity such that the unobtrusive measure of team coordination would correlate with a subjective measure of coordination as well as a measure of TMS expertise coordination. H2 posited that the developed measure would demonstrate discriminant validity such that the unobtrusive measure of team coordination would not correlate with a measure of psychological safety. One factor and four of the individual items demonstrated convergent validity with subjective coordination and TMS expertise coordination ($p < .05$). One factor and five of the items demonstrated discriminant validity with psychological safety ($p > .05$). Face validity was assessed using input from subject matter experts (SMEs) and an empirical literature review. Taken together, the measure of unobtrusive team coordination was partially validated.

H3 posited that both the subjective and unobtrusive measure of team coordination would predict team performance, which was examined using MLM regression analyses. First, a null model was fit to ensure clustering amongst team members. The null model was significant (p < .01) with an ICC value of .60. When examined individually, three of the items predicted performance. More specifically, team communication dispersion predicted performance, with t(170.26) = -2.52, p < .05 , ICC= .58, CI [-.017, -.002]. Next, Team keywords dispersion predicted performance, with t(189.04) = 3.54, p < .01 , ICC= .67, CI [.060, .221]. Lastly, Team role-specific information predicted performance, with t(189.96) = 4.07, p < .01 , ICC= .66, CI [.212, .625].

	Correlations			MLM Regression
Item	Subjective Coordination	TMS Expertise Coordination	Psychological Safety	Team Performance
Team Acknowledgements	+	+	+	
Team Acknowledgement Dispersion	+	+	+	
Team Questions	+			
Team Role-Specific Information Shared	+			
Team Keywords	+			
Team Role-Specific Information Shared Dispersion				+
Team Keywords Dispersion				+
Team Questions Dispersion	-	-	-	
Team Communication Dispersion	-	-	-	-

	Correlations			MLM Regression
Factor	Subjective Coordination	TMS Expertise Coordination	Psychological Safety	Team Performance
Factor 1	+		+	
Factor 2	+		+	+
Factor 3				+
Factor 4	-	-	-	-

Figure 2. Summary of Results

When examined across the four factors, three of the four factors predicted performance. Factor 2 predicted performance, with t(189.65) = 2.23, p < .05 , ICC= .63, CI [.006, .120]. Next, Factor 3 predicted performance, with t(189.53) = 2.90, p < .01 , ICC= .65, CI [.026, .147]. Lastly, factor 4 predicted performance, with t(168.24) = -2.53, p < .05 , ICC= .58, CI [-.016, -.002]. Subjective coordination did not predict performance (p > .05). Such results demonstrate a relationship between the developed measure of unobtrusive team coordination and performance as well as criterion-oriented validity of the developed measure (Cronbach & Meehl, 1955). As a result, H3 was partially supported.

H4 posited that when examined within the same model, the unobtrusive measure of team coordination would predict performance above and beyond the subjective measure of team coordination. When examining the three factors and subjective coordination within the same model, all three factors predicted performance above and beyond the measure of subjective coordination, ICC= .74. Within the model, factor 2 significantly predicted performance, with t(187.45) = 3.79, p < .01. Factor 3 significantly predicted performance, with t(187.06) = 6.30, p < .01. Lastly, factor 4 predicted performance, with t(189.72) = -5.29, p < .01. An ANOVA was then conducted to examine differences in the null model and the model with the level one predictors. The model with the level one predictors was significant when compared to the null mode, with $\Delta\chi 2$ (4) = 45.95, p < .001. Taken together, H4 was supported.

DISCUSSION

The results of the current study provide preliminary support for the RADSM process when developing systems-based measures, specifically a measure of team coordination. When examined individually and at the factor-level, the measure of unobtrusive team coordination partially demonstrated convergent and discriminant validity (H1-H2).

When looking at the individual items within the measure, three items (Team communication dispersion, Team role-specific information shared, Team role-specific information shared dispersion) predicted performance. The factors that predicted performance were clustered based on information sharing (factor 2), the dispersion of information sharing (factor 3), and the dispersion of team communication exchange (words and questions spoken; factor 4). As expected, factor 2 predicted performance such that increased information sharing predicted increased performance, which is supported by previous research that has identified communication and asking questions as elements of coordination that are related to increased team performance (Butchibabu, 2016; Kolbe, 2009; McCormack et al., 2017; Pinto & Pinto, 1991). Further, factor 4 predicted performance such that increased dispersion of team communication exchange (words and questions spoken) predicted decreased performance. However, the relationship between factor 3 and performance was not as expected. More explicitly, factor 3 predicted performance such that increased role sharing dispersion predicted increased performance. It is possible that while it is important for team communication exchange (factor 4) to be equally distributed, certain roles may require a greater degree of information sharing (factor 3) which would result in an inequal distribution of information amongst team members leading to increased performance. In support of that explanation, previous research has demonstrated that hierarchical communication patterns, centered around the leader, can impact team productivity and quality. In addition, leaders may benefit from sharing more information than they receive (Ehrlich & Cataldo, 2014). Such findings would underscore that communication patterns that facilitate positive outcomes may be impacted by team roles opposed to equal team communication distribution.

In addition, when both unobtrusive and subjective team coordination were put in the same model, the three factors of unobtrusive or subjective team coordination predicted performance while the measure of subjective team coordination did not (H8). Given that previous research has highlighted the need to understand differences in subjective and unobtrusive constructs given their unique benefits and limitations (Khaleghzadegan et al.,2020; Salas et al., 2015a), this finding highlights that although subjective and unobtrusive measures of the same constructs may be related, they can have independent and differing relationships with certain outcomes variables (Mesmer-Magnus& DeChurch, 2009). In addition, previous research examining organizational outcomes has demonstrated unobtrusive measures to be more robust predictors when compared to subjective measures (Baek & Ihm, 2021). Further, it could be that subjective or unobtrusive measures of the same construct map on to outcomes differently based on the data source of the outcome. For example, within the current study, an outcome variable that was perception-based may have demonstrated a relationship with the subjective measure of coordination as opposed to the unobtrusive measure of coordination. There are notable limitations to the current study which may have impacted findings, which are discussed below.

The current study has several limitations that are important to note in terms of both acknowledging certain confines of the research as well as to inform future work. To begin, while the study was designed to examine team processes (e.g., coordination) in a military environment, the current iteration of the study sample consisted mostly of civilian undergrad participants. Further, given that the teams consisted of individuals that were not a part of an established team, it is possible that elements of team behavior and team process may differ when examined within established teams. However, team coordination is a team process (opposed to an emergency state that may take longer to develop). As such, the behaviors and attributes selected as part of the measure were likely less impacted. Further, given that the examined relationships would likely be weaker in newly formed teams and that the current study demonstrated significant relationships, the current study may be under representative of the effect of the examined relationships.

Additionally, the current study utilized an observer measure of team performance. The observer rating of performance was highly driven by task completion within the missions, which may be different than the perceptions of team coordination. As a result, it is possible that the selected measure of team performance was biased towards the unobtrusive team coordination indictors, which resulted in the differences between the two measures of coordination and performance. Especially given that previous research has demonstrated a relationship between subjective team coordination and performance (Chang et al., 2017; Espinosa et al., 2004).

Lastly, issues with data collection severely minimized the ability to adequately execute the RADSM process as intended. Such issues limited the availability of the items to include within the unobtrusive team coordination measure as well as limited the ability to conduct more robust analyses. To begin, certain items within the initial unobtrusive measure of team coordination were not able to be included due to limitations because of data collection and technology issues. For example, proximity data and movement data were both collected but excluded as a result of issues with data collection and the quality of the data produced by the unobtrusive data sources. As a result, team coordination was only able to be examined using communication-based indicators of coordination. It is possible that the developed measure of unobtrusive team coordination may have seen additional significant relationships demonstrating construct validity and predicting performance had the other data sources and corresponding indicators been included in the analyses. In addition, issues with data collection resulted in data loss such that the sample size was impacted. The availability of a larger sample prevented the use of a preliminary dataset that was intended to be used to conduct the EFA. As a result, the PCA, EFA, and CFA were conducted on the same data, which doesn't represent best practices for factor analysis.

Further, issues with the Bluetooth wireless earpieces (e.g., disconnecting, noise interference, etc.) as well as substantial background noise impacted the quality of the audio data, all of which had impacts on the accuracy of the unobtrusive measure, especially given the developed unobtrusive measure was solely based on audio data. More explicitly, even though the audio files were mostly transcribed by hand, certain words, phrases, as well as large portions of the audio files could have been missed due to data quality issues. This would have a significant impact on all of the unobtrusive team coordination items. Lastly, in some instances where individual pieces of technology failed and there was missing data, cross-team averages had to be utilized in order not to exclude the entire team. Given the variations of communication across the roles, cross-team averages may not be accurately representative of the missing role. However, despite the data quality issues and missing data, the significant relationships from the collected audio data provide confidence in the quality of the developed measure.

In addition to the limitations and future research directions, it seemed pertinent to outline lessons learned given the novelty of unobtrusive data collection as well as the “file drawer” problem that exists within unobtrusive data measurement methodologies. More explicitly, when novel research methodologies are utilized, such as the development of unobtrusive measures utilizing technology, often there are elements of the research design that fail and therefore the results and subsequent lessons learned are never disseminated. Although the findings of the current study only partially validate the developed measure of unobtrusive team communication, both the novelty of the described approach and the best practices developed from the current study can still inform and advance the field.

To begin, it is important to note that some constructs are more difficult to examine unobtrusively. For example, certain behaviors that are more often attributed to implicit coordination would have been difficult to include in the developed measure. Specifically, behaviors such as anticipatory behaviors, which have been demonstrated to be indicators of coordination, often include an element of cognition that is currently difficult, if not impossible to capture using just unobtrusive data sources. As a result, it’s important to consider the available data sources and crosswalk those sources with attributes and behaviors in the literature in order to ensure attributes and behaviors selected can be captured with the data sources that are available.

Next, advantages of the unobtrusive data collection techniques include that they often take less time and effort to collect as large sets of data can be collected continuously with minimal effort or intervention. However, the processing of unobtrusive data can be incredibly time consuming when compared to subjective data sources. Despite the advancements in technology, AI, and data management and analytic capabilities, it can be difficult to process large amounts of unobtrusive data that requires cleaning and restructuring. Further, just because data are collected using unobtrusive data sources, such as different pieces of technology, doesn’t always translate to data that is useable and functional. For example, the commercial-off-the-shelf (COTS) technology used for the current study had several issues and limitations that greatly impacted the success and progress of the study as well as the quality of the data. For example, the Bluetooth earpieces used to collect the audio data often disconnected and as a result, much of the audio data was collected through each individual’s smartphone which decreased quality of the audio data. It is very likely that the items developed using the RADSM process were adversely impacted such that the audio recordings were not clear enough for accurate transcripts, which would have impacted all ten RADSM items. In addition to COTS technology, the current study used internally developed software programs to collect data. In many cases, there were issues with the internally developed software installed on the COTS technology. As a result, some data was not collected during the experimental paradigms, resulting in missing data.

As a result, a key lesson learned is to execute a robust pilot of the data collection and processing methodologies. More explicitly, the current study could have benefited from assessing the COTS as well as the data collection techniques and methodologies prior to the larger data collection effort. Despite the advances to technology that have occurred, even the most advanced COTS technology still can have limitations and issues, some of which can be specific to data collection use cases. In the case of the current study, it is likely changes would have been made to the COTS in order to minimize limitations and improve data quality. For example, within the current study, the study team may have opted for a plug-in microphone instead of Bluetooth earpieces which would have minimized the occurrence of disconnections. Additionally, the project sought to use multiple data sources (e.g., proximity data), however those data sources were also impacted by data quality issues but could have been potentially revised in order to maintain a larger breadth of unobtrusive data source options for the RADSM process. In addition, as part of the pilot process, pilot data should be processed, cleaned, and at least partially analyzed in order to identify issues in the data collection to analysis pipeline.

Taken together, although there are several advantages to using unobtrusive data, there also many challenges that are unique to unobtrusive data that can impact the collection, processing, and cleaning of the data. Piloting the data collection and the subsequent processing and analyzing process can provide opportunities to make adjustments prior to the full-scale data collection. Although there are certainly challenges with unobtrusive data sources, it's important to continue to explore new technologies and novel approaches in order to address current gaps within the literature and expand data collection and analysis possibilities. As technology continues to improve and more advanced unobtrusive or minimally intrusive data source are available, it will be critical to establish processes as well as best practices in order to ensure the collection of both high-quality and empirically rigorous data.

CONCLUSION

The current study explored the use of a systematic approach, the RADSM process developed by Orvis and colleagues (2013), to develop an unobtrusive measure of team coordination. As part of the RADSM process, the measure was developed, refined, and examined for validity. The current study also extended those findings to compare the developed measure with an established measure of subjective team coordination. In summary, the developed measure was partially validated and demonstrated key types of validity (e.g., convergent validity) across a majority of the developed measure indicators as well as factors. When examined with performance, both individual indicators and factors predicted performance. Specifically, factors related to information sharing, the dispersion of information sharing, and team communication exchange were demonstrated to predict performance. Further, the same three factors of unobtrusive team coordination predicted performance above and beyond the subjective measure of team coordination when in the same model. Despite the promising results, there are several limitations and lessons learned that may have contributed to the ability to fully validate the developed measure and see expected relationships within the data.

In summary, the current study encapsulates the complexities associated with both collecting data using unobtrusive data sources as well as developing measures from such sources. While technology is advancing, there are still many limitations to technology that makes leveraging unobtrusive data sources, instead of subjective perceptions, both difficult and time consuming. As a result, in addition to providing an overview of a systematic process an unobtrusive measure of team coordination, the current study seeks to draw attention to best practices and future research that can continue to grow and improve upon this line of research. The use of unobtrusive data sources will only continue to increase, and it's important the conceptual integrity of established constructs is maintained moving forward.

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