# What's *that* supposed to mean? Capturing Micro-Behaviors in Teams

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Future long-duration space exploration (LDSE) crews will require extensive coordination, cooperation, and team functioning as they face a myriad of challenges rooted in both taskwork and teamwork (Bell et al., 2015; Landon et al., 2018). While exposed to extreme conditions, crew members must navigate living and working together in prolonged confinement. Moreover, astronaut teams are becoming increasingly diverse, introducing significant variability in team composition. This increasing diversity, alongside traditional constraints of LDSE, introduces additional challenges into effective team functioning.

To date, most methods for capturing team functioning rely on self-report measures. Such measures are prone to several limitations, including but not limited to social desirability bias, halo effect, and leniency effects (Trull & Ebner-Priemer, 2013), which skew data and limit nuanced understandings of phenomena at play. Self-report measures broadly capture team functioning, lending the nature of such methods to identifying underlying "macro"-behaviors (i.e., behaviors that are long-standing and last over time). However, team functioning is far more complex than a series of macro-behaviors, rendering reliance on self-report data deficient for accurate measurement.

Recent research demonstrates the potential of alternative methods for capturing team functioning, such as speech and physiological data (Chaffin et al., 2017; Murray & Oertel, 2018). Consequently, these methods are more suitable for capturing micro-behaviors: brief, often unconscious expressions that affect the extent to which an individual feels included by others around them (Paletz et al., 2013). Micro-behaviors can be further classified into micro-aggressions (i.e., subtle, negative exchanges; Keller & Galgay, 2010) or micro-affirmations (i.e., subtle, positive exchanges; Kyte et al. 2020), both of which influence team functioning.

Due to the subtle nature of micro-behaviors, contextual factors have a significant impact when determining if it is aggressive or affirmative. Additionally, several iterations of micro-behaviors can have lingering effects on team interactions. For example, the use of “mm-hmm” by a crew member can function as both a micro-affirmation and micro-aggression. Specifically, it can be indication of active listening (i.e., micro-affirmation) or as an expression of annoyance (i.e., aggression) depending on the context in which it occurs. Auditory features (e.g., tone, frequency) can help delineate between the two forms; however, the contextual factors (e.g., previous interactions between team members, crew demographics) add a layer of complexity that render auditory features alone as insufficient to capture micro-behaviors.

Consequently, this paper seeks to provide a novel approach in which multi-modal data (i.e., auditory features and contextual features) are used in a random-forest model to better identify distinguishing characteristics between micro-affirmations and micro-aggressions. In turn, detected micro-behaviors are used to predict team performance, thereby demonstrating the value of capturing micro-behaviors as supplemental data to macro-behaviors.

## Method

Data were collected from 9, 4-person crews that participated in a simulated space mission in NASA’s Human Exploration Research Analog (HERA). As part of HERA, crews partook in 5 team interaction batteries (TIBs) in which crew members completed a decision-making task followed by a relational task. The former requires all crew members to engage in effective information sharing to solve a presented problem (e.g., select the best landing site of three) whereas in the latter, crews received questions to foster interpersonal relations (e.g., “what do you value most in a relationship?” “what is your most terrible memory?”; Aron et al., 1997).

Conversational data from the TIBs were analyzed in two parts: feature extraction and behavioral coding. To provide data for machine-learning models, lexicon-based features were first extracted using the Linguistic Inquiry and Word Count (LIWC; Kim et al. 2020) and STRESSnet (Yadav et al., 2018). Both LIWC and STRESSnet are commonly used to indicate the presence of various processes (e.g., linguistic, psychological, cognitive), thus providing the foundation of conversational speech data present during the TIBs. Acoustic features (e.g., tone, frequency) and sentiment features (i.e., valence of speech content) were also extracted to provide a comprehensive, feature-based dataset for initial analyses. Second, a group of 6 undergraduate students, trained by a Research Coordinator and Research Assistant, are coding the same interactions for each TIB. Students are trained to identify instances of micro-behaviors based on contextual factors that may not otherwise be captured by software (e.g., “mm-hmm” as dismissal or active listening). Coding is currently underway and will be complete by SIOP 2023. Coded data will then be added to existing models to further refine model performance.

## Results

Using random forest classification, various models were trained across 100 decision trees to classify the presence of micro-aggressions, micro-affirmations, and neither (e.g., neutral). Models differed in which features were included (e.g., lexicon-only, acoustic and sentiment, sentiment only). A random classifier model combining LIWC, STRESSnet, and acoustic features performed the best, with an F1-score of 55%. Once coding is complete, these data will be added to the models to further refine and better distinguish between micro-aggressions and micro-affirmations in teams. Presence of micro-behaviors as classified by the models will then be used to predict team performance during the TIB.

## Discussion

Initial results demonstrate that various linguistic and acoustic features are indicative of types of micro-behaviors that occur in conversations. Though analyses that included behavioral coded data are yet to be completed, these initial findings are promising. We posit that full results will demonstrate how rigorous methods using multi-modal data can better detect micro-behaviors rather than self-report data or unimodal data (e.g., coding alone, acoustics alone). Additionally, we hypothesize that these micro-behaviors will influence team performance over time. As such, we aim to present a deeper understanding of underlying, subtle behaviors impacting team functioning, paving a path forward to enhancing team performance in LDSE teams.

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