

Identifying Latent Processes in Multi-Modal Physiological Signals for Team Performance: An Exploratory Structural Equation Modeling Approach

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Abstract

Teams operating in complex, dynamic environments rely on coordinated interdependent action for mission success. Underlying these team interactions are latent processes that are commonly measured through self-report measures, but little is known about how physiological signals contribute to these latent processes within teaming environments. This study examined how physiological signals from 5-person teams load onto latent factors using exploratory factor analysis (EFA). Results revealed a two-factor structure: inter-beat interval (IBI), respiratory rate, and pupil diameter loaded onto an “arousal” factor, while oxyhemoglobin (HbO) and deoxyhemoglobin (HbR) loaded onto a “cognitive engagement” factor. A structural equation model (SEM) then evaluated whether these factors predicted team and aggregated individual performance ratings. Arousal significantly predicted both outcomes, whereas cognitive engagement was non-significant. These findings suggest that respiratory and neural activity contribute most distinctly to their respective latent factors, though only arousal was a reliable indicator of team and aggregated individual performance.

Keywords

SEM, team performance modeling, multi-modal data analysis, human teams

Introduction

Teams are increasingly used across several domains to complete complex tasks. Within these teams, there are underlying latent processes that manifest in individuals and facilitate interdependent action toward the team’s goal. Although prior research has measured these processes through self-report measures (Delice et al., 2019; Mathieu et al., 2019), it remains unclear how each physiological signal contributes to these latent processes within teaming environments. Through physiological signals, we can better validate the connection between physiology and latent processes to highlight the dominant physiological signals from individuals in dynamic team settings. To address this, we investigated how physiological signals from 5-person teams load onto latent factors and how much each signal contributes through exploratory factor analysis (EFA). From the EFA results, we then utilized a structural equation model (SEM) to evaluate whether these latent processes could predict the teams’ overall mission performance ratings and the average rating of all individuals’

performance. We investigated whether physiological indicators would capture distinct aspects of latent processes within teammates, and how that affects overall team performance.

Background

Within teams, individuals’ latent states fluctuate as they work interdependently with teammates. Teams involve two or more members working interdependently toward a common goal (Salas et al., 1992) and possess both explicit processes (e.g., verbal communication) and unobservable

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processes (e.g., cognitive load) (Salas et al., 2017). Due to the dynamic nature of teams, it is difficult to capture these unobservable processes that are latent to individuals. Prior research has utilized self-report measures to quantify how these latent processes change throughout a team's lifespan (Delice et al., 2019; Mathieu et al., 2019). Although the relationship between physiological signals and team performance has been studied (Yadav et al., 2025), it remains unclear which physiological signals are most effective in revealing latent processes within a teaming environment. Furthermore, existing research using physiological data has largely focused on single modalities to measure latent processes (Cui et al., 2012; Palumbo et al., 2017; Shiraishi & Shimada, 2021) and has not combined multi-modal physiological measures to represent individuals' physiological states holistically. To measure these latent processes, structural equation modeling (SEM) identifies latent variables from observed measures and can be utilized to predict outcome measures. Although SEM has been used with single physiological measures to predict latent processes like fatigue (Srinivasan et al., 2024), no research has applied it to multi-modal physiological data both to assess individuals' latent processes and to predict team outcomes. This study investigated the following two research questions:

RQ1: What are the dominant physiological signals that contribute most to latent processes within teams?

RQ2: Can these latent processes be used to predict a team's performance outcomes?

Approach

We collected training data from 12 Fire Support Teams Sessions (FiST) from 8 teams, each session composed of 5 members: Lead, Joint Terminal Attack Controller (JTAC), Fire Support Officer (FSO), Forward Observer/Mission (FOM), and Forward Observer Assistant (FOA). Simulations covered 3 phases: preparation (battlespace awareness), planning (coordinating indirect fires), and execution (immediate suppression). Scenarios required dynamic sub-team formation to manage parallel and sequential subtasks, increasing complexity in execution and team interactions. The mission goal was for teams to identify, defend against, and engage enemy targets through coordinated indirect fire support across the preparation, planning, and execution phases. All team members' physiological data (electrocardiogram (ECG), electroencephalogram (EEG), eye-tracking, and functional near-infrared spectroscopy (fNIRS)) were collected, synchronized to a global timeline, and down-sampled to 1 Hz. Raters assessed mission performance and individual performance

for each member on 4-point scales (1=Low, 4=High) then agreed on a single score for each performance. Team-level individual performance was the mean of the five members' rating for that run.

The collected physiological data were grouped per team member and aggregated into 150-s epochs, at the individual-level across 12 sessions and 5 team members. The 150-s aggregation window was based on our prior findings (Lyu et al., 2026), which utilized the same dataset and found this epoch length yielded optimal classification performance for team outcomes. This 150-s window balances temporal resolution with data stability, providing sufficient granularity to capture physiological changes. From the modalities collected, respiratory rate, respiratory amplitude, alpha/beta/theta/delta power, inter-beat interval, pupil diameter, gaze entropy, HbO, and HbR were extracted. To address multicollinearity among the physiological signals, respiratory rate, beta power, inter-beat interval, pupil diameter, gaze entropy, HbO, and HbR were kept for the following analysis, ensuring that the retained variables provided independent contributions to the model.

Each physiological sensor underwent individualized pre-processing pipelines to enhance data quality. EEG signals were processed using bandpass filtering, notch filtering, and SSP algorithms for artifact removal (eye movements and cardiac artifacts). IBI and Respiration underwent signal quality assessments to identify periods of unusable data. fNIRS data underwent spectral analyses to identify reliable versus unreliable signals, isolating valid data for modeling. Eye tracking data were processed using Pupil Labs software. Gaze data were systematically denoised and mapped to relevant environmental objects, facilitating high-quality behavioral analysis.

To validate whether these physiological signals loaded onto factors, we first conducted an EFA to evaluate the factor loadings of each physiological signal. Then, we utilized the latent structure derived from EFA to evaluate whether these latent processes could predict team and individual performance in the SEM. We utilized full information maximum likelihood to account for missing data and Maximum Likelihood with Robust Standard Errors (MLR) estimate to account for non-normality. These data were analyzed in Rstudio using the *lavaan* package.

Outcome

Bartlett's test for sphericity was significant, indicating that the observed variables were correlated with each other, $p < .05$. From the scree plot analysis, we retained 2 latent factors from the physiological signals. We utilized a Principal Axis Factoring (PAF) to measure the shared variance between variables to identify the underlying latent constructs with an

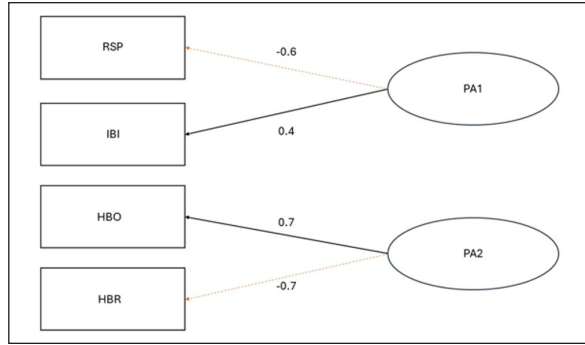


Figure 1. Exploratory factor analysis diagram.

oblimin rotation so the constructs could correlate. Factor 1 consisted of respiratory rate (-0.60), inter-beat interval (0.40), and pupil diameter (0.24), indicating an autonomic arousal factor. The opposing signs of the Factor 1 loadings reflect the directional relationship of each signal to sympathetic nervous system activation. IBI increases as heart rate slows, indicating lower sympathetic arousal, consistent with its positive loading. Conversely, respiratory rate increases with arousal, yielding a negative loading relative to the factor's orientation. Factor 2 consisted of the two fNIRS measurements of HbO (0.70) and HbR (-0.70), suggesting a brain response factor. We removed pupil diameter from Factor 1 due to weak factor loading below 0.40 (Hair et al., 2010). The result is shown in Figure 1. Overall, the two factors explained 20% of the shared variance.

For the SEM model, we constrained both inter-beat interval and HbO to a parameter estimate of 1. This constraint

allowed estimation of the latent factor variances for predicting the outcome measures. Overall, the SEM model showed a good fit, 0.99 in Comparative Fit Index (CFI), 0.97 in Tucker-Lewis Index (TLI), 0.026 in Root Mean Square Error of Approximation (RMSEA), and 0.012 in Standardized Root Mean Square Residual (SRMR). These metrics suggest overall good model fit (Kyndt & Onghena, 2014). As shown in Figure 2, the loading of respiratory rate on Factor 1 was statistically significant, $\beta = -.15$, $p < .001$. For Factor 2, HbR was statistically significant, $\beta = -.383$, $p < .001$. In predicting team mission performance, Factor 1 was statistically significant, $\beta = .11$, $p < .001$, but Factor 2 was not statistically significant, $p > .05$. Similarly, for the individual performance ratings, Factor 1 was statistically significant, $\beta = -.09$, $p < .001$, whereas Factor 2 was not statistically significant. Overall, the arousal factor predicted the team's performance and aggregated individual performance.

Conclusion

We identified two distinct processes within large-scale teams through their physiological states and provided evidence that Factor 1 predicting both team and aggregated individual performance in this exploratory investigation. Addressing RQ1, EFA identified respiratory rate and IBI as the dominant signals for arousal and HbO and HbR for cognitive engagement. We labeled Factor 1 as *Arousal* because respiratory rate and IBI shared autonomic variance. This supports previous research in which cardiac and respiratory activity relate to arousal associated with overall team task demands (Mathôt, 2018; Yi & Palmer, 2026). We labeled Factor 2 as *Cognitive Engagement*

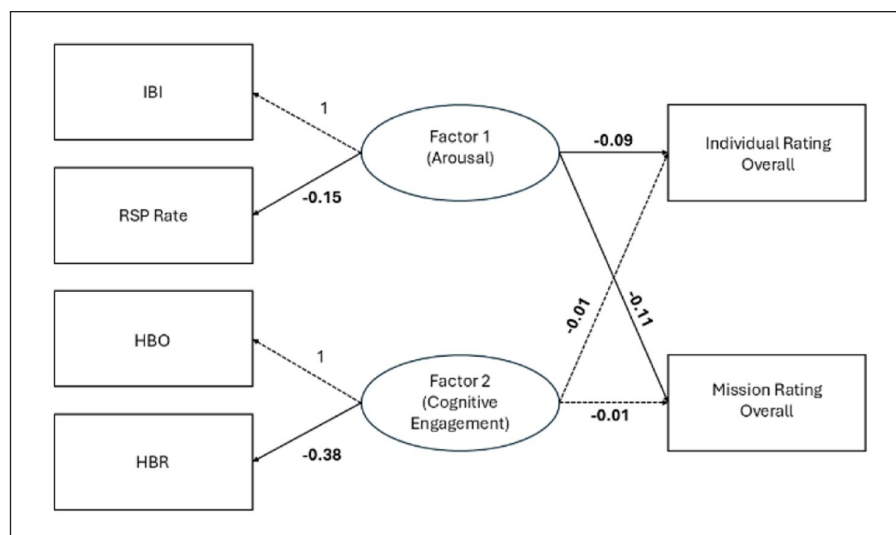


Figure 2. SEM path diagram (bolded numbers are significant estimates).

because both fNIRS channels loaded onto the same factor. Since fNIRS can measure changes in cortical oxygenation associated with cognitive processing (Sharmin et al., 2024), this suggests that the factor captured cognitive demands in dynamic team settings to accommodate for task demands.

This study showcased a holistic measure of different physiological measurements for each individual to determine the dominant signals that are capturing distinct latent factors. Our results were similar to those of a previous multi-modal study of team performance classification, which found that respiratory features were the top features in their machine learning pipeline (Yadav et al., 2025). Addressing RQ2, arousal significantly predicted both team-level outcomes while cognitive engagement was not significant. These findings further support respiration as one of the more dominant physiological signals within teaming environments. In addition, this also supports the notion that arousal, as a latent process, can predict team outcomes. The negative estimate between arousal and overall individual performance suggests that higher arousal may hinder task performance. This pattern is broadly consistent with the descending limb of the Yerkes-Dodson curve, where performance decreases once arousal exceeds an optimal point. However, the present linear model does not test or confirm a curvilinear relation (Teigen, 1994). For mission performance, arousal positively predicted mission performance, suggesting high levels of arousal may facilitate coordination at the team-level. This concept also applies within the team-level in which teams may require some self-regulation mechanism to calibrate arousal to optimize performance. This divergence between overall individual and mission performance may suggest that higher arousal leads to individuals initiating more coordinated joint action with teammates. This may enhance team-level outcomes but at the expense of individual task performance. Overall, this study investigated which physiological signals are dominant toward latent processes and how these latent processes may also predict team outcomes.

This study has three main limitations that suggest directions for future research. First, this was an exploratory investigation with only a single time-point outcome measure and a limited sample size, precluding observation of performance changes across the mission. Future studies should incorporate multiple subtasks or indicators of progress to track how latent processes evolve throughout a team's lifespan, with a much larger sample size. Second, the present SEM did not account for the temporal autocorrelation inherent in physiological time-series data. Future work should utilize dynamic SEM to incorporate temporal autocorrelation across time as it relates to latent factors. Third, physiological signals were segmented into 150-s windows, rendering these observations non-independent. Future work should employ multilevel SEM to properly account for this interdependence. Furthermore, the latent factors identified in this study reflect collective states at the individual level, which may not fully capture the collective

dynamics underlying team performance. Together, the two factors explained 20% of the shared variance via Principal Axis Factoring (PAF). This low variance is a by-product of not including team-level physiological signals and interdependencies into the model. Future work should incorporate team-level physiological measures such as entropy-based features, dynamic time warping, or cross-recurrence quantification, to link team-level physiological states to collective team outcomes.

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