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Multi-level Team Coordination Dynamics during Simulation-Based Medical Team Training

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Abstract

Team coordination is essential for effective performance during critical, stressful events. To better understand processes and states involved at multiple levels of team coordination, we assessed the correspondence between low- and high-level coordination in teams participating in simulation-based medical team training. We computed a measure of low-level team coordination with Multidimensional Recurrence Quantification Analysis, applied to arm movement, heart rate, and skin conductance data. High-level team coordination was captured by annotating video recordings for explicit and implicit, information and action coordination. Three linear mixed-effects model were run, each predicting a type of low-level coordination, based on high-level coordination annotations, accounting for multiple observations per team. Our findings showed that, compared to periods without annotated coordination, explicit- and implicit- information coordination corresponded to significantly different low-level team coordination across each of the studied modalities. Further research is required to assess additional factors related to the temporal variability observed in low-level coordination.

Keywords: team coordination; team cognition; dynamical systems; psychophysiology; recurrence quantification analysis

Introduction

Team coordination plays a vital part in the performance of teams working in highly complex and stressful environments, such as teams operating in military (Leedom & Simon, 1995) or health care contexts (Kolbe et al., 2013). These teams have to effectively handle demanding circumstances, during which sudden shifts in workload and task complexity can occur, which often require high-stakes decision making under time pressure (Salas et al., 2007). To minimize errors in decision making, and optimize team performance, effective team coordination is crucial (Helmreich & Schaefer, 1994).

In team research, *coordination* has been described as a collective team cognitive skill (Cooke et al., 2007), which entails "orchestrating the sequence and timing of interdependent actions" (p. 363, Marks et al., 2001). Studies following this definition have mostly focused on the more readily observable team processes and states involved in team coordination, representing *high-level team coordination*. Examples at this higher level are explicit team coordination, which involves actions and behaviors to coordinate joint actions or gain mutual understanding, and implicit team coordination, which involves actions and behaviors to anticipate needs related to joint action or mutual understanding without overt communication (Chang et al., 2017; Kolbe et al., 2013; Rico et al., 2008). However, over the last years, a growing number of studies have shown that, by incorporating the complex systems definition of coordination (Kelso, 1994), team coordination may also be assessed at a lower level of interaction.

From this perspective, *low-level team coordination* refers to the covariation of signals (e.g., physiological, neural, movement) among team members, as they collaborate to address changes in their shared working environment (Gorman & Amazeen, 2010; Kelso, 1994). Coordination based on these signals is considered low-level because it often occurs at smaller scales of analysis relative to the entire team (Fusaroli et al., 2016), and typically occurs unintentionally between team members (Knoblich et al., 2011). A variety of signals and methods can be used to measure low-level coordination, several of which have been found to reflect unique, high-level coordination processes and states (see Halgas et al., 2022; Kazi et al., 2021). For example, team coordination between electrodermal activity (EDA) of team members was related to monitoring of collaborative learning processes (Dindar et al., 2019; Haataja et al., 2018), and coordination in movement was found to predict collaborative problem solving performance (Wiltshire et al., 2019). Moreover, transitions, or substantial changes in the level of coordination, for team heart rates and EDA were found to be indicative of breakdowns in team coordination (van Eijndhoven et al., 2023).

Thus, previous research on team coordination, as well as interpersonal coordination (e.g., Richardson et al., 2005; Schmidt et al., 1990), has provided theoretical groundwork for adopting this dynamical multi-level perspective of team cognition and coordination (Gorman, 2014). Accordingly, recent frameworks have been developed to further advance the empirical methodologies and understanding of the dynamical nature of team coordination (e.g., Gorman et al., 2017; van Eijndhoven et al., 2023; Wiltshire et al., 2022). Unlike more traditional approaches to team cognitive processes that focus on static and linear interpretations (e.g., Cannon-Bowers et al., 1993; Klimoski & Mohammed, 1994), dynamical approaches interpret team cognition as continuously changing over time, as a response to their working environment. Instead of focusing on the individual or collective cognitive structures, the systemic team structure is assessed, which may span different system levels (e.g., low and high), and occur at different timescales (e.g., seconds for low-level physiology, minutes for high-level team processes

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and states; Cooke et al., 2013; Wiltshire et al., 2022). In the current study, we consider team coordination from the low and the high level, thereby synthesizing coordination theory and methodology from both more traditional (e.g., Marks et al., 2001) and more dynamical team research (e.g., Wiltshire et al., 2022).

Gaining an understanding of the processes and states involved at multiple levels of team cognition, such as high-level coordination reflected by low-level coordination, is a prerequisite to understanding effective team performance (Cooke et al., 2007; DeChurch & Mesmer-Magnus, 2010; Kolbe et al., 2013). However, different operationalizations to measure low-level team coordination, relate not only to high-level team coordination, but also to other higher-level team processes and states (e.g., team cohesion, Mønster et al., 2016; collaborative learning, Pijeira-Díaz et al., 2016). Studies assessing how to distinguish specific high-level processes and states from others (e.g., implicit from explicit high-level coordination), by examining low-level team coordination, are scarce. Consequently, there is a need for better insight regarding whether and how different low-level signals and coordination measure combinations correspond to specific high-level processes and states (Halgas et al., 2022; Wiltshire et al., 2022). This would also enable us to capture team coordination in a quicker and less labor-intensive way (i.e., computationally) than would be the case with human observers (i.e., manually), which are unlikely to be present in real-life teamwork scenarios. Subsequently, we can further examine the processes involved in effective and ineffective team coordination.

Thus, in the current exploratory study, we aim to assess how low-level team coordination corresponds specifically to high-level team coordination. By examining the correspondence between low- and high-level coordination, and the possibility to computationally distinguish high-level team coordination from processes and states unrelated to team coordination, we seek to support teams operating in critical situations. Especially in such situations, effective team coordination, and subsequently, team performance, can make a crucial difference.

Method

Our study utilized data collected during a simulation-based medical team training course. Low-level team coordination was based on arm movement, photoplethysmogram (PPG; reflecting blood volume change arising from heart beats), and EDA (reflecting electrical conductance properties of the skin) signals, that can be measured in real time (i.e., with wearable devices) and quantified to reflect coordination with multi-dimensional recurrence quantification analysis (MdRQA; Wallot et al., 2016). We distinguished periods with and without high-level team coordination and annotated the type of high-level team coordination (explicit/implicit-action/information; Kolbe et al., 2013). The data set used in the current paper is part of a larger research project. More detailed information, including additional details regarding the participants and experimental procedure, can be found in the preregistration on the Open Science Framework (https://osf.io/q236r).

Participants

For the current study, we analyzed data of 14 teams participating in simulation-based medical team training (100 females and 3 males; lowest age range = 18-24; highest age range = 55-64). Data for each team was collected during one or two scenarios, depending on participant consent. This resulted in data collection during a total of 25 scenarios, of which one scenario was excluded due to poor physiological signal quality. Additionally, for one wearable, arm movement data quality was poor across two scenarios, leading to exclusion of this data. Teams ranged from five to seven members, all employed in an obstetrics and gynecology department. Each team consisted of nurses, a resident, and a gynecologist. Some teams included student nurses and midwives.

Experimental Procedure

We collected our data during a simulation-based medical team training that was already provided by the hospital. Participants of this training course were informed about the study three to seven days in advance. On the day of the training, participants were asked if they had questions regarding the research, and if agreed upon, to sign a consent form. Next, the researchers provided them with Empatica E4 wearable devices (Empatica Srl, Milan, Italy) that collect PPG (64 Hz), EDA (4 Hz), and arm movement (acceleration across three axes; 32 Hz). Participants then completed a demographic questionnaire. A GoPro Max 360 camera (GoPro, Inc., California, United States) was used to collect 360° video and audio data, and the training would continue as usual, without the presence of the researchers.

During each scenario, a medical case was simulated, using actors (student doctors), a hybrid birthing simulator, and a neonatal mannequin. The medical case would either involve the delivery of a baby in breech position (N = 13), or a pregnant woman with pneumonia that would go into septic shock (N = 12). We analyzed scenarios from the moment the whole team was present, until the end. Subsequently, a scenario lasted 8 min and 18 s on average (SD = 2 min 11 s). Scenarios took place in a real delivery room with all the usual medical equipment. All scenarios required team coordination to achieve a positive patient outcome, and involved an unforeseen medical calamity that teams had to respond to.

After each simulated scenario, prior to the debrief, participants completed a questionnaire regarding team and task work (Johnson et al., 2007), team adaptive performance (Marques-Quinteiro et al., 2015), team potency (Guzzo et al., 1993), and perceived stress (Amirkhan, 2018). The hospital's trainer rated the teams' performance (Frankel et al., 2007). Afterwards, the trainer did a training debriefing with the participants. Once all scenarios were done, the participants had the opportunity to ask questions about the research, concluding the experiment.

Analyses

Low-level Team Coordination

Arm movement, PPG, and EDA were used to estimate low-level coordination, as they can easily be captured in real time with wearable sensors. This is an important characteristic that enables in-situ support in dynamic working environments based on low-level team coordination. Arm movement was collected with the wrist worn E4 wearable's accelerometer. This sensor captures movement along three axes X, Y, and Z, which represents the axis' magnitude and direction of acceleration. To preprocess this data, we followed steps suggested by Lehmann-Willenbrock and Hung (2023). First, each axis was standardized using z-scores. Next, magnitude was calculated: $Magnitude = \sqrt{X^2 + Y^2 + Z^2}$. This step enables us to obtain a unified measure of the amount of overall arm movement (i.e., magnitude), with which we can compute low-level team coordination. Lastly, magnitude was downsampled to 4 Hz.

To obtain heart rate from PPG data, we applied Python library Neurokit2's function ppg_clean() (Makowski et al., 2021), which implements Elgendi et al.'s (2013) preprocessing method. An additional bandwidth filter [0.7-3.5 Hz] was implemented with Python library HeartPy's filter_signal() function (van Gent et al., 2019). Subsequently, a sliding window technique was used to calculate heart rate in beats per minute. Heart rate was determined based on 120 s of cleaned PPG data, and recalculated at every 1 s. As a result, a continuous series of heart rate values at 1 Hz was obtained. Heart rate was calculated utilizing the process() function of HeartPy. For some windows, this function was unable to compute heart rate. On average, per scenario, 3.61% of windows (SD = 9.47) had this issue. These missing values were supplemented with heart values that E4 software automatically generates. Finally, a rolling mean (5 s) sliding window was applied to slightly smoothen heart rate spikes (noise) in the data.

To preprocess the raw EDA signal, it was first resampled from 4 Hz to 40hz. This allowed for the application of a low-pass filter with a 3 Hz cutoff frequency and a 4th order Butterworth filter, following the standard Neurokit2 implementation. This step was implemented with the eda_process() function. Moreover, this function extracted the phasic component of the EDA signal, which is found to represent event-related sympathetic activity (Benedek & Kaernbach, 2010), and used in previous team coordination research (e.g., Ahonen et al., 2018; van Eijndhoven et al., 2023). After filtering, the data was resampled back to 4hz for further analysis. The phasic data timeseries were further used to compute EDA-based low-level team coordination.

Sliding window MdRQA was applied to generate a continuous measure of low-level team coordination, based on each of the three signals. MdRQA is a recurrence-based method to extract coordination patterns of multiple variables over time (Wallot et al., 2016). The input is embedded in a multidimensional phase space. For example, per team, the EDA timeseries of each team member is embedded into a multidimensional phase space, after which recurrent points are determined. Recurrent points and repeating recurrence sequences are used to quantify teams' coordination dynamics (for a complete overview of metrics see Wallot & Leonardi, 2018). Points of recurrence are indicated if their similarity falls within a set threshold: the radius.

We applied the mdrqa() function of the Python library MultiSyncPy (Hudson et al., 2022) on windows of 60 s, and reran MdRQA with a window step of 1 s. The radius parameter was set for each individual signal time series following Wallot and Leonard's (2018) guidelines. While it is possible to examine other properties of the recurrence plot, similar to van Eijndhoven et al. (2023) and Gorman et al. (2020), the current paper focused on Determinism (DET). Per scenario, we obtained one timeseries with DET data for each signal sampled at 1 Hz. This metric is a quantification of the proportion of recurrent sequences (i.e., diagonal lines on the recurrence plot). DET ranges from 0 to 1, with values close to 0 indicating irregularity in the signals (i.e., few repeating patterns), and values close to 1 indicating regularity within the signals (i.e., many repeating patterns). Moreover, a timeseries with a wider range of DET values indicates more flexibility within the coordination of the physiological and movement signals, whereas a smaller range would indicate more rigidity. See Figure 1 for an overview of the different types of generated low-level team coordination.

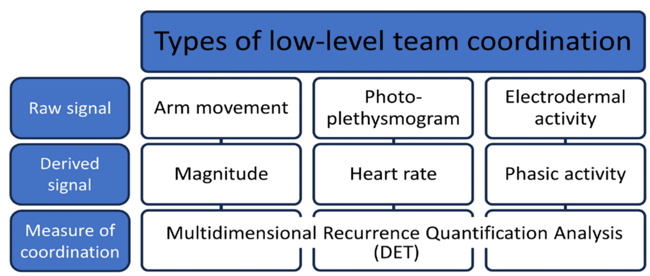

Figure 1: Overview of low-level team coordination types.

High-level Team Coordination

Audiovisual recordings were manually annotated for high-level team coordination with the Framework for Observing Coordination Behavior in Acute Care Teams (Kolbe et al., 2013). Figure 2 shows a visualization of the framework.

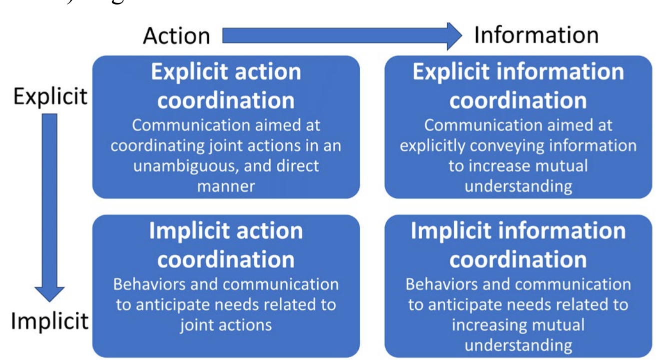

Figure 2: Overview of high-level team coordination types (adapted from Kolbe et al., 2013).

We adjusted Kolbe et al.'s (2013) code examples to the context of the current study. The framework consists of four quadrants, organized along two dimensions. Each quadrant represented a different type of high-level team coordination (see https://osf.io/5rdtk) for a detailed description and the codebook). High-level *explicit action* coordination included, for example, communication regarding instructions or planning, whereas *implicit action* coordination included monitoring of other team members or providing assistance. Whereas *explicit information* coordination entailed, for example, information requests and evaluation, *implicit information* coordination contained the provision of information without request and team members gathering information within their environment. For the purpose of the current study, we focus on the quadrant-level annotations of team coordination.

In our annotation process, we also annotated the absence of high-level team coordination when no such behavior was present. This enabled us to examine whether a distinction exists in low-level coordination between periods with and without high-level coordination. Making such a distinction computationally would allow for the provision of timely support regarding team coordination in an more automated way. Two independent coders assessed the presence of each code at a per second rate, resulting in two timeseries of high-level team coordination at a resolution of 1 Hz per scenario. Coders had a background in biomedical science, cognitive science, and artificial intelligence. As part of their training, coders, the researcher that compiled the codebook, and the trainer of the simulation-based trainings, extensively reviewed the coding scheme. Next, coders started annotation, and discussed their annotation differences and ambiguity in the codebook after annotating ~5%, ~10% and ~20% of the scenarios. Intercoder reliability was established based on the annotations of ~20% (N = 5) of the audiovisual scenario recordings. Cohen's Kappa (κ) was computed as a measure of reliability, which indicated substantial agreement. Subsequently, this subset was expanded to an ~50% subset (N = 12), after which reliability was recalculated. Table 1 provides an overview of the obtained κ values.

Table 1: Overview of intercoder reliability measured as Cohen's Kappa (κ).

	20% subset κ	50% subset κ
Explicit action	.70	.79
Explicit information	.69	.78
Implicit action	.74	.76
Implicit information	.79	.86
Quadrant average	.73	.80

In cases where code consensus was not reached, a third-party adjudicator, which was the experimenter that created the codebook and trained the annotators, made the final decision. As a result, one unified high-level team coordination timeseries was generated per scenario.

Assessing Low- and High-level Team Coordination

To assess how low-level team coordination corresponds to high-level team coordination, three linear mixed-effects models were run, one for each of the low-level team coordination types as the dependent variable (i.e., arm movement, PPG, and EDA determinism). In all three models, high-level team coordination was included as a fixed effect, which consisted of five levels (explicit action, explicit information, implicit action, implicit information, no annotated coordination). Based on these levels, four dummy variables were created. The level 'no annotated coordination' was used as the reference category.

For each of the three models, we tested an increasingly complex random effects structure following a minimal to maximal modeling building approach. First, we accounted for the multiple observations per team as a random intercept. Next, we added 'Scenario' as a random effect, to account for the nesting of scenarios within teams, and then evaluated including Time as a random effect. To identify the simplest model structure that provided the best fit across models, we assessed the changes in marginal R^2. In addition, we applied the anova() function of the R library Stats (R Core Team, 2013) and evaluated the chi-square outcome metrics. If the more complex random effects structures were found to perform better, we would further increase model complexity and reevaluate the best fit. Results of the simplest model structures with the best fit are reported in the results section. The additional results are available on the Open Science Framework (https://osf.io/m2cdn). The models were implemented, utilizing the lmer() function of the R library Lme4 (Bates et al., 2015). Subsequent models' assumptions were checked with the check_model() function of the R library Performance (Lüdecke et al., 2021). Assumptions were met.

Results

We fitted three linear mixed-effects models to predict each type of low-level team coordination with high-level team coordination. For all three models, the best fitting model had a minimal random effects structure, accounting only for the multiple observations per team as a random intercept. Exclusion of scenario from the random effects only slightly changed the significance for the fixed effects.

The linear mixed effects model predicting low-level team coordination based on arm movement (M = .64, SD = .15) had a total explanatory power of 13% (conditional R^2 = .13). The fixed effects alone explained 0.4% of the variance in low-level coordination (marginal R^2 = .004). The model's fixed and random effects estimates can be found in Table 2 under 'Arm movement-DET model'. We observed a statistically significant and positive effect of explicit information coordination on coordination in arm movement (b = 0.03, p < .001). These findings show that, as compared to the absence of any annotations, in the presence of explicit information coordination, DET increased with 3%. Implicit information and action-related high-level coordination effects were non-significant.

Table 2: Results showing the relationship between high-level and low-level team coordination.

	Arm movement-DET model		PPG-DET model		EDA-DET model	
Fixed effects	*b (p)*	95% CI	*b (p)*	95% CI	*b (p)*	95% CI
Intercept	**0.63 (< .001)**	[0.60, 0.66]	**0.76 (< .001)**	[0.74, 0.79]	**0.39 (< .001)**	[0.33, 0.48]
Explicit action	-0.003 (.461)	[-0.009, 0.004]	-0.004 (.316)	[-0.01, 0.004]	0.003 (.431)	[-0.005, 0.01]
Explicit information	**0.03 (< .001)**	[0.02, 0.04]	**-0.03 (< .001)**	[-0.04, -0.02]	**0.01 (< .05)**	[0.001, 0.02]
Implicit action	-0.01 (.153)	[-0.02, 0.004]	0.01 (.074)	[-0.001, 0.03]	0.02 (.061)	[-0.001, 0.03]
Implicit information	-0.003 (.417)	[-0.01, 0.005]	**-0.03 (< .001)**	[-0.04, -0.02]	**0.02 (< .001)**	[0.001, 0.03]
Random effects	Variance	*SD*	Variance	*SD*	Variance	*SD*
Intercept	0.003	0.054	0.003	0.055	0.02	0.14
Model fit	Conditional R^2	Marginal R^2	Conditional R^2	Marginal R^2	Conditional R^2	Marginal R^2
	.13	.004	.13	.008	.40	.001

Another type of low-level team coordination was based on PPG data, from which we derived heart rate. The model predicting this type of low-level team coordination (M = .76, SD = .16) had a total explanatory power of 13% (conditional R^2 = .13), the fixed effects alone explained 0.8% of the variance in low-level coordination (marginal R^2 = .008). The model's fixed and random effects estimates are displayed in Table 2, under 'PPG-DET model'. We observed a statistically significant and negative effect of explicit information coordination (b = –0.03, p < .001) and implicit information coordination (b = –0.03, p < .001) on PPG-DET. These results indicate, that in the presence of both explicit and implicit information coordination, as compared to periods of no annotations, low-level coordination decreased with 3%. The fixed effects explicit and implicit action coordination were non-significant.

Phasic data, derived from EDA, was used as a base to calculate a third type of low-level team coordination. In predicting this low-level coordination type (M = .39, SD = .22), the linear mixed effects model had a total explanatory power of 40% (conditional R^2 = .40). The fixed effects alone explained 0.1% of the variance (marginal R^2 = .001). Fixed and random effects estimates of this model are listed in Table 2, under 'EDA-DET model'. We observed a statistically significant and positive effect of explicit information coordination on EDA-DET (b = 0.01, p < .05). In addition, a statistically significant and positive effect of implicit information coordination on EDA-DET (b = 0.02, p < .001) was found. In other words, in the presence of explicit information coordination, as compared to periods of no annotations, there was a low-level coordination increase of 1%. This increase was 2% for the presence of implicit information coordination. Both action coordination-related fixed effects were statistically non-significant.

Discussion

In this paper, we assessed how low-level team coordination corresponds to high-level team coordination during a simulation-based medical team training course. We found that, across low-level team coordination types, explicit or implicit information coordination resulted in significantly different DET values. More specifically, during periods of annotated explicit information coordination, DET based on arm movement was on average 3% higher than during periods without annotated high-level team coordination. An increase in DET indicates an increase in recurring patterns. This finding is consistent with previous work suggesting that gestural alignment (which includes arm movement) during conversation facilitates mutual understanding (e.g., Rasenberg et al., 2020). No significant arm movement-DET change was found during periods of implicit information coordination, which involves behaviors and communication to anticipate mutual understanding-related needs. Unlike explicit information coordination, the implicit counterpart represents personal rather than intrapersonal communication, which may correspond less to gestural alignment, providing an explanation for the non-significant result.

Both PPG- and EDA-DET model outcomes indicated explicit and implicit information coordination as significant fixed effects. During periods of these types of high-level team coordination, signal regularity based on EDA was observed to be larger than during periods where no annotations were made. Conversely, signal regularity based on PPG was identified as smaller, indicating a decrease in repeating patterns. This difference in results could be a reflection of the correspondence between joint attention, which facilitates mutual understanding (Roessler, 2005), and coordination based on EDA and PPG signals. Consistent with this interpretation, in a study by Brouwer et al. (2019), participants were instructed to listen to the same auditory stimulus: an audiobook, in which a repeated short stimulus was incorporated. Participants were told to either pay attention to the story presented in the audiobook or to the short stimulus. They found that participants compared to other participants related to the same attentional group exhibited significantly higher degrees of uniform change in phasic EDA (i.e., low-level coordination), than when compared to participants who focused on the other auditory stimulus. No such relationship was present for low-level coordination based on heart rate. In other words, Brouwer et al.'s (2019) findings indicate that EDA signals exhibited more regularity or uniformity, when participants attended to the same stimulus (i.e., joint attention). In our study, we found a similar correspondence, indicating that EDA signals exhibited more regularity or uniformity, when participants engaged in information coordination to increase mutual understanding. This similarity suggests that when participants engage in processes and states facilitating mutual understanding, such as joint attention, EDA-based coordination becomes more uniform or regular. Similar to Brouwers et al.'s study, we also found that when participants engage in processes and states facilitating mutual understanding, PPG-based coordination does not become more uniform or regular.

Notably, in all three models, no significant effects were found for action-related high-level coordination. This indicates that explicit and implicit behaviors and communication regarding joint actions do not specifically and consistently correspond to DET values above or below the DET values associated with no coordination annotation. This finding could be related to the flexible nature of coordination. Previous team literature has indicated that teams coordinate flexibly to carry out specific functions required to meet emerging task demands (Gorman & Amazeen, 2010; Stachowski et al., 2009). To achieve the same task demands, patterns of coordination may differ. Thus, it could be the case that more flexible low-level coordination is required to achieve action-related high-level team coordination. This type of high-level coordination is more directly focused on achieving task demands by coordinating actions, than information-related coordination, indicating that action-related team coordination does not necessarily have to be associated with a consistent level of DET values. To assess the different low-level coordination patterns that may be associated with action-related high-level coordination, future research could, for example, consider the examination of trajectories of low-level coordination in a growth modelling approach (cf., Wiltshire et al., 2019). Such analyses might provide more insight into how temporal patterns in low-level coordination change over time during action-related high-level coordination.

Though we observed several interesting model results, the amount of variability that the fixed effects alone accounted for was weak. Our results imply that high-level team coordination accounts for some variability in low-level coordination, but that there are other factors to take into consideration. Given that low-level team coordination has been found to not only capture high-level team coordination, but also other team processes and states, future research should build on this literature to expand the assessment at the higher-level. For example, previous research found that PPG- and EDA-based low-level coordination related to affective behaviors (Gordon et al., 2021) and team cohesion (Mønster et al., 2016), which could be considered as a factor in our models. Low-level coordination derived from movement, was related to e.g., group membership (Miles et al., 2011), attributions of rapport, and entitativity (Lakens & Stel, 2011). Nevertheless, based on our continuous measures of low-level coordination, and annotations of high-level coordination, we did observe consistent results across mixed-effects models.

Additionally, in our data collection and analysis, we encountered challenges as part of the health care context, that required us to make methodological decisions. For example, occasionally, multiple sub-teams were operating within a team, leading to multiple high-level team coordination annotations for the same point in time. To be able to capture all annotations across high-level quadrants, for each team we created separate variables for each type of high-level coordination. This meant that at the same timepoint, an annotation of each quadrant could be present. With this approach, we were able to apply the mixed linear models, while acknowledging the occurrence of multiple sub-teams engaging in different types of high-level team coordination. We also found that while teams participated in two simulation-based medical scenarios, teams did not consist of exactly the same members for each scenario. From the first scenario to the second, a minority of team members who were more active changed to a more passive role and vice versa. We expect these small changes in training teams to be similar to teams operating in hospitals, that assemble and disassemble based on occurring patient and hospital needs. Given that the majority of team members and roles remained the same, we did not account for this in the models. Finally, our data sample represents an obstetrics and gynecology department of one hospital. This led to the inclusion of only three male participants. Though this might be representative for other obstetrics and gynecology departments, more research needs to be conducted to assess whether there are differences with other departments that include more men.

Conclusion

In our study, we examined team coordination at both a lower and higher level. We synthesized coordination theory and methodology from both more traditional and more dynamical team cognition research. Subsequently, we assessed the correspondence between low- and high-level coordination. Notably, we found that low-level coordination reflecting phasic EDA signal regularity was significantly higher and regularity based on heart rate was significantly lower during periods of high-level explicit and implicit information coordination, as compared to periods of no annotated coordination. Regularity based on arm movements was significantly higher only during explicit information coordination. Such knowledge can be incorporated in computational approaches to identify, and distinguish between, higher level processes and states of team coordination. This enables us to gain a better understanding of the processes and states involved at multiple levels of team cognition, such as coordination, which is beneficial for enabling in-situ monitoring and real-time support. Ultimately, this work is foundational for the real-time provision of support to teams operating under critical conditions. Especially for these teams working, monitoring and supporting team coordination, and subsequently, team performance, can make a meaningful impact.

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