Multimodality studies that measure Team Processes: a literature review

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Abstract

Interest in understanding team interaction and team dynamics in fast-changing environments has substantially increased in multiple disciplines, such as educational science, psychology, and computer science. This is probably because team dynamics are one of the most important drivers for high levels of team effectiveness. To capture the actual, in-situ dynamics of teams the importance of using process measures has been emphasized. In the past decade, more and more researchers have found the benefits of using sensor technology to capture team dynamics as this provides the opportunity to constantly assess what is going on and eases the data gathering and analysis process. Combining at least two process measures allows for creating a more complete picture of team dynamics. The goal of this study is to create an overview of the situation at this moment of literature that captures these team dynamics with at least two process measures. The main research question for this paper, therefore, is "What is the current state of studies using at least two process measures to capture team dynamics over time in the context of teams?". To create this overview, seven empirical publications that used at least two process measures to capture team dynamics over time in the context of teams are systematically reviewed. From the found literature, the following focus points were identified: (1) reasons for adopting such a research design; (2) the use of analytical techniques; (3) how theory was used; and (4) the future research agenda.

Keywords: team dynamics, multimodal designs, behaviour, sensor technology

Multimodality studies that measure Team Processes: a literature review

Teams are the foundation of most organizations these days (Wiese & Burke, 2019) which also drives the sheer amount of research conducted to understand what makes a team effective. Team dynamics (i.e., how people interact in a team) is one of the most crucial factors for the effectiveness of a team (Schneider et al., 2021). Therefore, interest in team dynamics and interaction has recently increased in several disciplines. Understanding team dynamics is important because these processes can help us understand what makes for an effective team (Wiese & Burke, 2019). Research, as well as practice, can benefit from exploring team interaction processes (Endedijk et al., 2018). For example, understanding team interactions within an organization can help to improve team effectiveness and therefore enhance the effectiveness of the organization (Wiese & Burke, 2019). Another example is team interactions in student teams to better understand their learning activities and facilitate ways of successful learning (Noroozi et al., 2020). To understand team dynamics, it is crucial to look at these processes over time (Noroozi et al., 2020). Taking this process perspective will provide a more complete picture of the constructs investigated (Sjøvold, 2022).

Previous research often focused on the use of self-report surveys and questionnaires and direct observation with the use of trained observers (Sjøvold, 2022) to examine team interaction processes. Self-report surveys usually study static points in time and thus give few insights into the processes that happen over time (Lehmann-Willenbrock, 2017). To get a completer understanding of team dynamics it is needed to move from more human-based observation methods to methods that identify team processes over time. So called process measures are continuous measures of team interaction processes over time, for example, observation (Schneider et al., 2021). It is challenging to collect such process measures but new data collection tools such as sensor technology have eased capturing this type of data (Schneider et al., 2021). Such sensors allow human interaction to be measured and analysed efficiently and cheaply (Sjøvold, 2022). An example of such a technology is a wearable sensor, they can for example capture physiological state, speech patterns and body posture (Schneider et al., 2021). These new techniques also make it possible to measure interaction features without interfering with the natural interaction process (Fischer & Järvelä, 2014).

Recent developments in measuring team interaction over time are the combination of multiple process measures to look at team dynamics. With sensor technology, data collection is easier and more detailed, which eases the process of combining different measurements such as skin conductance and other social interaction features. The combination of different process measures can provide information about behavioural processes because of the continuous measurement of physiological data (Endedijk et al., 2018). Research that combines at least two process measures in the context of teams is innovative, and only few studies have adopted such a design. Therefore, this systematic literature review can make an important step in gaining more insights into team dynamics and contributes to the existent literature by creating an overview of the studies that used and combined at least two process measures over time in the context of teams. To arrive at this overview the focus is on: (1) reasons for adopting such a research design; (2) the use of analytical techniques; (3) how theory was used; and (4) the future research agenda. From this overview, the main findings, practical implications and limitations and strengths of this study are presented.

Theoretical Framework

Team dynamics

Teams are defined as “distinguishable sets of two or more people who interact, dynamically, interdependently, and adaptively toward a common and valued goal/objective” (Salas et al., 1992). The term ‘team dynamics’ in this study is defined as the interactions between team members that are constantly shaped and influenced by all team members (Delice et al., 2019). Interactions are a series of ongoing behavioural processes and actions that occur over time (Lei et al., 2016; Stachowski et al., 2009). Team members influence each other in a variety of ways, for example through interruptions, and turn-taking, but also the content of their interaction plays a role (Endedijk et al., 2018). Continuous capturing of these behavioural processes and actions is required to better understand team dynamics. This continuous capturing of interaction dynamics can be done through multimodal designs including the use of so-called process measures.

Multimodality & process measures

To measure team dynamics, it is pivotal to capture the process of how teams interact over time. Team dynamics can be best understood by continuous observation of the interaction process (Sjøvold et al., 2022), According to Klonek et al. (2019), the methods and approaches need to include the temporal aspect over which such a process unfolds. Processes can be measured with for example video observation and sociometric badges that record body movement, proximity, and skin conductance (Eloy et al., 2019; Noroozi et al. 2020). Gathering and studying these data might help to get a better understanding of cognitive, motivational, and emotional processes over time during team interaction. This is important because this provides insights into team processes and can help facilitate effective and efficient teams (Noroozi et al., 2020).

To get a holistic picture of team dynamics different aspects of the interactions between team members must be investigated (Noroozi et al., 2020). Many of the noval data modalities do not provide direct information about certain processes and therefore the use of many data channels is needed (Haataja et al., 2018). The combination of different measurement data is called multimodality. Multimodal data can for example consist of self-report questionnaires, audio-video recordings, and physiological data (Noroozi et al., 2020). Important to emphasize is that multimodality does not necessarily measure processes. In the scope of this study, however, it is important that the studies did use at least two modalities to collect process measures. For example, sensors that capture electrodermal activity combined with a sociometric badge (which includes Bluetooth, an infrared sensor, an accelerometer, and a microphone) allow for the analysis and comparison of moments of high- and low arousal

(Endedijk et al., 2018). To reveal the dynamic processes of teams these different continuous streams of data must be combined and therefore a multimodal approach is necessary.

Sensor technologies for gathering process data

One method that has been more often applied lately to capture team dynamics and interaction is video capturing and coding (Noroozi et al., 2020). Although video capturing and coding offer new insights about how team members effective interact in situ, and thus elevates our understanding of effective team processes, it is labour-intensive. Video observation of team interaction entails time-consuming data processing by trained observers (Sjøvold et al., 2022). In the last decade, however, many other technologies have been developed to measure human and team interaction which is cheaper and less labour-intensive. Wearable sensors, such as sociometric badges or the Empatica E4-wristband, are examples of such technologies. With a sociometric badge, objective data such as speech patterns and body movements can be collected (Kim et al., 2012). The Empatica E4-wristband can measure electrodermal activity (EDA), which is an indicator for identifying moments of high arousal (Endedijk et al., 2018). Combing the measurements of these different technologies enables detailed exploration of social interaction (Carter et al., 2015; Endedijk et al., 2018). For example, Endedijk et al. (2018) combined data of sociometric badges with skin conductance and video data to analyse the structure and content of team interactions. This gave further insights into effective team interactions but also has the added value of combining sensor technology with more traditional data (Endedijk et al., 2018).

Methods

An integrative literature review (ILR) was done to identify the status of studies using at least two modalities that collect process measures over time in the context of teams, examining team dynamics. An ILR is a systematic way of collecting research within various fields of study (Cho, 2022). ILR is the most common review type in Human Resource

Development (HRD) and aims at being interdisciplinary by searching multiple sources (Cho, 2022). This approach was chosen because (1) the topic of this study is upcoming and pioneering; (2) this approach can contribute to a new theoretical framework; and (3) it is a topic of study that multiple disciplines deal with, namely educational science, psychology, and computer science. This ILR was conducted in line with the PRISMA guidelines for systematic reviews (Moher et al., 2009). In this study, the aim is to review and present an overview of the studies so far that have combined multiple process measures to understand team dynamics, unravel the potential of such designs, and come up with future research suggestions.

Search keywords and databases

This ILR was conducted in the period February 2022 to June 2022. In the identification phase, a database search was done using Scopus, Web of Science (WoS), and Google Scholar. A start was made with a broad search combining “multimodality” or “multichannel” with “team”, “interaction”, “dynamics”, “technology”, “sensors” and “process measure”. *Multimodality* was found to be a generic term and caused many irrelevant sources to appear. Combining *multimodality* with relevant terms such as *team dynamics* and *technology* led to more relevant results for the scope of this study. The relevant keywords named above were combined with Boolean operators to search for relevant literature on *Scopus*, *WoS* and *Google Scholar*. An asterisk (*) was used to capture all possible words with the same stem of the keywords of interest. The searches on Scopus, WoS and Google Scholar were conducted in March 2022.

Parallel to this, articles from 2010-2022 journals on Small Group Research and Group & Organization Management were gathered. A visual representation of the study selection process can be found in Figure 1.

Additional search parameters

Various search parameters were specified further to arrive at relevant results for this review. First, only peer-reviewed publications were included to ensure the reliability of the sources. Second, only English-written articles were included since this is the predominant language in science. Third, since the reviewed field of study is relatively new and upcoming only the most recent literature was studied (i.e., the time was limited to publications from 2005 through 2022)

Identification of relevant literature

The results from the search were screened. Titles, abstracts and when necessary, the full text were inspected and only articles relevant to the scope of this review were selected. All relevant studies were also scanned for relevant cross-references. Reasons that publications were excluded from further analysis were articles that did not (1) use at least two modalities which capture process measures to study the different foci; (2) study team interaction or team dynamics; and (3) report empirical findings on the topic (conceptual, methodological, and theoretical publications). In addition, duplicates were removed. Both conceptual and methodological studies were used in the review to support the results of empirical studies, but not in the analysis.

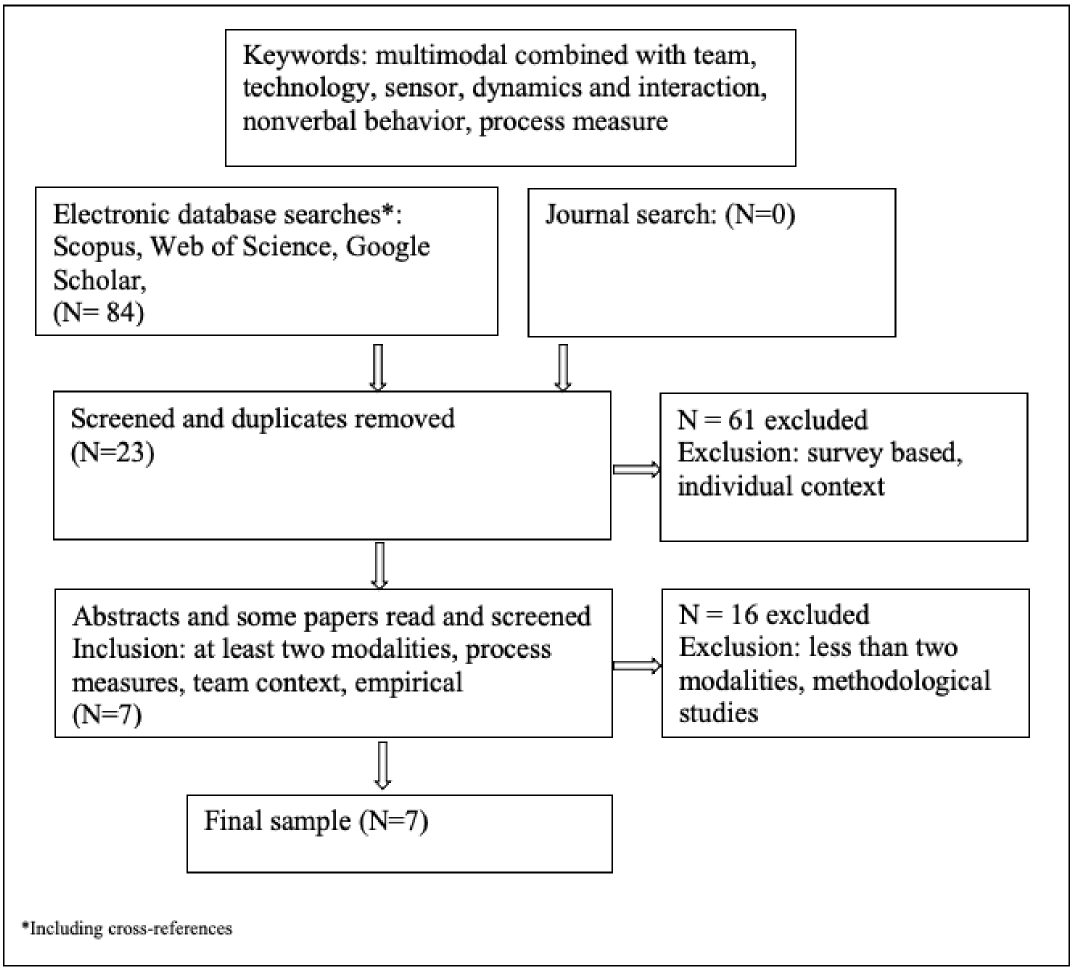

Figure 1. Search process

Identified themes for the Review

Based on the framework the identified themes for this review are as follows:

- Reasons for adopting this research design
- Different analytical techniques used
- The use of theory
- Future research suggestions

The results section follows this order. In section 4.1 several different reasons for adopting such a research design for small group research are highlighted. In section 4.2 the different analytical techniques used are summarized. In section 4.3 the role of theory in this research design is investigated. In section 4.4 current challenges and future research suggestions are summarized.

Results

This integrative literature review included seven articles. The articles included in this review to answer the different questions are presented in Table 1

Table 1

Study Characteristics

Source	Research purpose	Country	Sample characteristics	Field of study	Type of data modalities	Constructs measured	Analytical technique
Dindar, Alikhani, Malmberg, Järvelä, & Seppänen (2019)	The relationship between shared monitoring of collaborative learning processes and physiological synchrony between the collaborating group members	Finland	1 group of 3 students	Educational science	Video, audio, EDA	Collaborative learning	Multidimensional recurrence quantification analysis (MdRQA); Pearson correlation analysis
Endedijk, Hoogeboom, Groenier, de Laat, & van Sas (2018)	Capture the structure and content of team interactions of medical teams at moments of high arousal during a simulated crisis	Netherlands	22 groups, 92 first-year master's students (tech med), Mean age 22.4; 56% female	Educational science	Sociometric badge, skin conductance recording, video, teacher ratings of performance	Team effectiveness in crisis	Series of repeated measures MANOVAs; dependent sample t-test; independent sample t-tests

Malmberg, Haataja, Seppänen, & Järvelä (2019)	How monitoring occurs in computer-supported collaborative learning during a collaborative exam situation	Finland	12 high-school students; 4 groups; Mean age 15.5; 74.2% female	Educational science	Video, skin conductance recording	Metacognitive monitoring	Qualitative content analysis; pearson correlation; single session index (SSI)
Haataja, Malmberg, Dindar, & Järvelä, (2021)	Examines how the pivotal role of monitoring for collaborative problem solving is reflected in interactions, performance, and interpersonal physiology	Finland	University students; 19 groups of 3; Age M=27.84; 57,2% female	Educational science	Shimmer 3GSR+ sensor (EDA recording), video, task performance measures	Collaborative problem solving	Multidimensional recurrence quantification analysis (MdRQA); Friedman test; repeated measures ANOVA
Haataja, Malmberg, & Järvelä, (2018)	How students in a group monitor their cognitive, affective, and behavioural	Finland	High-school engineering students, 16 groups of 3	Educational science	Empatica E3-sensor, video	Metacognitive monitoring during collaborative learning	Qualitative video analysis, physiological concordance (PC), SSI

	processes during their colleboration						
Spikol, Ruffaldi, Landolfi, Cukurova (2017)	Insights into which features of student group work are good predictors of team success in open-ended tasks with physical computing	Europe (Sweden, Italy & UK)	6 groups of 3 students; Age M=20; 5.6% female	Computer science	Video (face & hand tracking), Arduino IDE, Audio	Predictors of team success	Cross-validation
Wiltshire, Hudson, Lijdsman, Wever, & Altzmueller (2021)	Understanding dynamics of team interaction	Netherlands/ germany	1 group of 7 people; management team of tech company; Age M = 41.3; 29% female	Cognitive science	Rhythm badges (audio), OpenBeacon sensor (proximity), video	Team dynamics	Dynamic complexity analysis, video analysis

Reasons for adopting this research design

Table 1 shows that a study design that includes at least two modalities for collecting process measures is applied in a variety of different fields, such as educational science, computer science and cognitive science. This implies that in multiple (interdisciplinary) fields there is a great deal of potential for using such a study design to enhance our understanding of team dynamics. The results in Table 1 show that of the seven studies, five are within the field of educational sciences. Another one of the studies was done within computer science but was also focused on student team dynamics. The last study that was found took place within cognitive science and focused on the team dynamics of a professional management team. Constructs measured ranged from collaborative learning, and collaborative problem solving to metacognitive monitoring processes during collaborative learning and team success. Hence, in a variety of different fields, there might be potential to adopt such a research design to answer important questions. Within the papers, several reasons for adopting such a multimodal, multi-process-measures design could be identified.

Firstly, the main reason for adopting this design in educational science studies is that multimodal process data hold the potential to reveal a more complete picture of the structure of team interactions. With the use of sensor technology, moments of high arousal can be measured objectively (Endedijk et al., 2018) in addition to more subjective self-report measures. From those high arousal moments, we can get further insights into what happens during moments when a person is not able to cope with the demands of the environment (Endedijk et al., 2018). In the context of teams, this can give insights into what structure of the team is most effective and how people adapt to situations (Endedijk et al., 2018). Also, rich information about how people monitor and regulate collaborative learning can be revealed by using this design (Haataja et al., 2021). It is hard to observe with the naked eye whether there is synchrony between members of a group when this is not verbally expressed

(Malmberg et al., 2019) and therefore using objective and multiple measures is important. Synchrony refers to the relation between the physiological responses of interacting individuals as they perform a collaborative task (Henning et al., 2009). This can provide information about physiological reactions and learning processes (Malmberg et al., 2019) and give insights into physiological synchrony among group members and collaborative learning processes within a team. All these different types of data and insights eventually provide a more complete picture of team interactions.

Second, in the field of computer science, this study design is used to make use of new tools and techniques that can capture different types of data from complex learning activities (Spikol et al., 2017). The shift to the use of more online learning and the use of new sensor technologies means that diverse types of data about learners' interactions, such as computer vision, audio and biometric data have become available. These so-called 'learning analytics' enable to predict the success of groups based on multimodal features automatically (Spikol et al., 2017). This can provide insights into practice-based learning (Spikol et al., 2017). Thus again, also in the field of computer science, this study design is used to provide a more complete picture of team interactions, specifically team learning.

The third field of study where this design has been used is that of cognitive science. The main reason for this was again to advance the understanding of team interaction (Wiltshire et al., 2021), which connects with the main reasons to adopt such a design in the other fields. Information about team communication and interaction patterns was gathered to identify transition points (i.e., changes in team member energy and engagement). These types of data provide important insights into team dynamics across multiple domains, such as business, aerospace, healthcare, and science (Wiltshire et al., 2021). It can become more clear what teams are doing and what they could change in their behaviour or attitude to become more effective. Real-time feedback can be used to optimize team performance because team members will have objective information about their role within the team and their contributions (Wiltshire et al., 2021).

In these studies, it was found that most research with this study design is being done within educational science. The potential for this design within educational science is mostly about understanding how students learn together and if there is equal participation in these processes as well as studying how teams learn collaboratively. Both in the educational sector, as well as in the other domains, critical points in collaboration can be identified with the use of sensor technology. New insights that were retrieved as opposed to a single modality design are for example what happens during moments of high mental effort, and the prediction of learning outcomes based on Multimodal Learning Analytics (MMLA).

Analytical techniques

Table 1 shows that a study design that includes at least two modalities for collecting process measures is analysed with different analytical techniques, such as Multidimensional recurrence quantification analysis (MdRQA), MANOVAs, t-tests qualitative content analysis, cross-validation, Pearson correlation analysis and dynamic complexity analysis. This implies that there is not (yet) a standard technique that is used when applying such a study design. The results in Table 1 show that two of the seven studies use MdRQA as an analytical technique (Dindar et al., 2019; Haataja et al., 2021). This technique looks at the repetition of values over time in a synchronously measured set of signals and shows how groups differ in their dynamics (Dindar et al., 2019). All the other studies use different analytical techniques to arrive at an answer to their research question. Within the papers, several reasons for adopting a certain analytical technique could be identified.

The studies that have been done in educational science have used several different techniques, namely, MdRQA, MANOVAs, t-tests, single session index (SSI) (sum of positive correlations across a learning session divided by the sum of the absolute value of negative correlations across the session) and qualitative content analysis. MdRQA appeared twice in different studies. The reason this technique was used is that MdRQA has been developed to reveal complex systems and is a promising approach that can be used to study group dynamics in collaborative contexts (Dindar et al., 2019). According to Dindar et al. (2019) MdRQA has added value to research about socially shared regulation of learning. It is one of the few methods that can quantify the synchrony between more than two signals (Haataja et al., 2021).

The other three studies that were done in the field of educational science made use of repeated measures MANOVAs, t-tests, and qualitative content analysis. To analyse the relations between different variables in the study of Endedijk et al. (2018) a series of repeated measures MANOVAs were conducted. For variables with different or too small sample sizes, a t-test was conducted. MANOVA is a common statistical technique to determine differences in multiple dependent variables over time, again capturing the dynamics of how the team interacted.

Furthermore, Table 1 indicates that several studies used multiple analytical techniques for their analysis. Combinations of qualitative content analysis to analyse the video recording and correlation analysis for the physiological data are used in studies that study the construct of metacognitive monitoring processes (Haataja et al., 2018; Malmberg et al., 2019). Moments where the physiological data showed peaks were investigated in more detail using the video. Physiological concordance (PC) was another method that was used to analyse physiological data. PC is an index for the physiological synchrony of a group. Haataja et al. (2018) were the first to use this approach in learning research. Wiltshire et al. (2021) used dynamic complexity analysis, a method for the analysis of complex systems. A heatmap is created and thereafter compared with what happened in the video recording with this technique. This way structural changes in networks are visualized (Wiltshire et al., 2021).

The study in the field of computer science used cross-validation to analyse the gathered data. Cross-validation is a common technique that divides the data into two segments: one is used to train a model and the other to validate the model (Refaeilzadeh et al., 2009). This specific technique is used because the goal of this research is finally to train a General Linear Model Regression model that can provide the grading of students' group design outcomes automatically (Spikol et al., 2017).

In conclusion, there is no standardization of analytical techniques used in most of these studies. Two studies that researched collaborative problem solving both made use of MdRQA(Dindar et al., 2019; Haataja et al., 2021), however in the other five studies no similarities were found between the research questions and the analytical techniques used. Haataja et al. (2018) argue that new methods will ease the process of finding meaningful events in these datasets, but that currently, efficient techniques are lacking. Often already known analytical techniques are used to analyse the data (e.g., MANOVAs, t-tests), even when multiple process measures are combined. When more studies adopt such a research design, more consistency in analytical techniques might occur. Haataja et al. (2021) suggest using MdRQA as a method because it can quantify the synchrony between more than two signals.

Theory-based or Theory development?

Table 1 shows that a variety of different concepts have been used and enriched which also implies that this set of studies has used and built upon a diverse set of theories. An important question to answer regarding these results is how the theory was used in these studies, especially given the novel and innovative measurement techniques that have been used as it might imply to our existent theories do not match with the novel approaches taken in the studies as they are often developed based on survey research. Accordingly, the different studies were reviewed to understand how the theory was used and in what field of study these theories are grounded. Three distinctive categories were observed: (1) theories within educational research; (2) theories within psychology; (3) theories within neuropsychology.

The first category consists of studies that used studies from former educational research in their theoretical framework (Dindar et al., 2019; Haataja et al., 2018; Spikol et al., 2017). Earlier research on collaborative learning suggested that socially shared regulation of learning is a dynamic process (Hadwin et al., 2017). Dindar et al. (2019) concluded that process measures are therefore necessary to investigate these processes. Until now these processes have been neglected because of the lack of methodological ways to measure them. The current study investigates these processes by identifying physiological markers of shared monitoring with the use of video data and EDA data. When comparing video observation data with the physiological data of the EDA sensor, the results revealed that shared monitoring of learning progress might be reflected as physiological synchrony (Dindar et al., 2019).

Haataja et al. (2018) started with the model of self-regulated learning (Winne et al., 1998). This theory states that in addition to metacognition and cognition, behaviour and effect are also central components in the regulation process. In earlier studies, it was found that successful groups consist of students that monitor their own and other students' task progress and interests (Näykki et al., 2017). It can be argued that physiological synchrony may be informative in exploring monitoring in collaborative learning (Haataja et al., 2018). The current study builds upon this by investigating how students monitor cognition, affect and behaviour using observational and physiological data.

Spikol et al. (2017) focus on models of social learning to investigate project-based learning activities. Due to the challenges surrounding the tracking of the learning processes research on this topic is rare, as it is hard to measure with existing standardized measurement methods (Blikstein & Worsley, 2016). MMLA provide opportunities to overcome these challenges by using high-frequency multimodal data. Therefore, this study uses MMLA to collect diverse streams of data to potentially predict group success (Spikol et al., 2017).

In the second category, studies drew upon theory within psychology (Endedijk et al., 2018; Haataja et al., 2021; Wiltshire et al., 2021). Endedijk et al. (2018) investigate how combining sociometric data, physiological data and video data can reveal more information about team interactions. They focus on how members of a group interact during moments of high arousal as this might explain performance (Endedijk et al., 2018). The unobtrusiveness of physiological measures with sensors holds benefits in collaborative settings, however more empirical work is needed to show if they relate to relevant processes in socially shared regulation of learning (Hadwin et al., 2018). Haataja et al. (2021) are motivated to explore whether characteristics of monitoring interaction are reflected in physiological data. They do this by building upon theories of regulation in collaborative learning (Hadwin et al., 2018) and investigate how valence and equality of participation in monitoring interactions relate to collaborative problem-solving performance, physiological arousal, and physiological synchrony (Haataja et al., 2021). Theory suggests that physiological arousal can reflect how capable students are in their learning process (Pijeira-Diaz et al., 2018). Malmberg et al. (2019) took these results as a starting point for investigating if these EDA peaks also reflect how students monitor their progress.

The work of Wiltshire et al. (2021) is motivated by the dynamical systems theory approach to teams (Gorman et al., 2017), a theory within neuropsychology. In their study, Wiltshire et al. (2021) combine theory on phase transitions with Rhythm Badge data to improve research on team dynamics. Seeing teams as dynamic systems helps to get a better understanding of the temporal evolution of team and task work behaviours (Wiltshire et al., 2021).

These results suggest that researchers of different fields use a variety of theories to investigate team interaction processes. This can be seen as a strength since different perspectives can help to create a holistic picture of team interactions (Schneider et al., 2021). However, current theories do not connect directly to the use of innovative measurement techniques. Researchers primarily used previous research as a starting point for investigating team interaction processes, but these theories often do not match the novel sensor technology used in the research. Previous research is often based on self-report measures, the novel approaches often measure physiological data. The link between this physiological data and certain team interaction processes often still consists of assumptions, this is something future research should investigate more. As such, the studies often were able to provide a more in-depth understanding of how the processes (that were assumed in many theories) unfold.

Future research suggestions

Some challenges and opportunities for future studies that include at least two modalities for collecting process measures were mentioned in the seven reviewed studies. Findings show that current studies primarily focus on collaborative learning processes (e.g., Dindar et al., 2019; Haataja et al., 2018; Haataja et al., 2021; Malmberg et al. 2019). In future studies, collecting multimodal data from different team dynamic aspects might help to capture other social processes that arise during team interaction. These different aspects could for example include communication, performance, and group composition (Schneider et al., 2020). This study design has the potential to reveal complex team processes in all kinds of disciplines, for example, healthcare, aviation, or management teams (Noroozi et al., 2020; Schneider et al., 2021).

Next, the data in the current studies were often gathered in simulated situations (Endedijk et al., 2018; Haataja et al., 2021; Wiltshire et al., 2021) this might cause a novelty effect not seen in other real-life contexts (Haataja et al., 2021). Therefore, the approach taken in these studies might also be used to gather real-life data to get more reliable and generalizable results. Malmberg et al. (2019) conducted the study in a real-life exam situation, this study shows the potential to use multimodal process measures in the field. For example, giving real-time feedback to companies which provides opportunities for effective real-time monitoring of team interactions.

For this to work, interdisciplinary collaboration is needed between computer science, cognitive science, and educational science. The technological advancements needed for sensors-based multimodal research in the fields of cognitive and educational science come from computer science since programming skills are needed to develop these techniques (Lehmann-Willenbrock & Allen, 2018). These technological advancements include, for example, eye movement tracking, brain activation, skin conductance, and other bio-physiological signals (Järvelä et al., 2019). Such technological advancements come with some issues regarding data processing since the amount of data gathered with such techniques is rather large (Sjøvold et al., 2022). Tools for handling such large amounts of data and machine learning can help to identify patterns in group dynamics (Sjøvold et al., 2022). The core interdisciplinary challenge is finding ways to challenge computer scientists to consider fundamental new questions and find solutions to these (Lehmann et al., 2017).

Another shared suggestion for future research from the studies is that there is a need to collect more data from multiple groups in different contexts to reach generalizable conclusions. In the current research, there is often a focus on one or multiple groups in one context. Multiple groups need to be studied in different contexts to collect more data in future research.

Lastly, a suggestion for future research is the implementation of more and other measures. Combining multiple process measures has to potential to reveal a more holistic picture of the conditions in which such team processes occur (Haataja et al., 2021).

Multimodal data originates from different channels for example, self-report, video recordings, and physiological data (Järvelä et al., 2019). Based on the research question and the behaviour under study, the choice of process measures is to be made.

Discussion

In this study, a systematic literature review was conducted resulting in a review of seven papers to create an overview of current studies using at least two process measures over time in the context of teams. Four themes were specified based on the results by looking at the similarities and differences between the studies. These four themes are (1) reasons for adopting this research design; (2) different analytical techniques used; (3) the use of theory and (4) future research suggestions. In the following paragraphs, the main insights from the study, some practical implications, the added values of this study design, and the limitations are discussed.

Principal findings

The results of this systematic literature review propose several opportunities for future multimodal studies that collect process measures in the context of teams. First, it is necessary to point out that the findings consist of seven empirical studies that adopted this specific research design. This is a remarkably low number and means there is a possibility for more empirical studies of this kind. During the literature search, a lot of literature reviews were found that expressed the need for more empirical work with this research design and the use of a new form of technology (Noroozi et al., 2020; Sjøvold et al., 2022; Schneider et al., 2021). They emphasize that this can advance our scientific knowledge on collaboration and tell us the strengths of these connections. It can also help to develop valid assessment tools that can adapt to the most common collaborative scenarios (Schneider et al., 2021). Thus, multiple fields of research such as educational science, psychology and computer science can benefit from further research on this topic.

From the results, another finding that stood out in the literature search phase is that journals on Small Group Research, and Group & Organization Management from 2010 to 2022 did not include any studies with this multimodal research design. Again, literature reviews that emphasized the need for more empirical work with this design were found, but few empirical studies implemented it. This can be because when the need for more empirical research was established the COVID-19 pandemic caused problems with the collection of data. The pandemic caused a shift to online remote working which hindered data collection in offline situations. However, the pandemic also may have made an opportunity for the collection of different types of group interaction data, namely online group interaction. In digital environments, a lot of cognitive, metacognitive, motivational, and emotional data is generated (Noroozi et al., 2020). The current technologies such as sociometric badges are now mainly used in offline situations. The use of these types of interaction data in online environments again calls for more technological advances and more research to further explore the interaction between individuals.

In most studies, a lot of assumptions were done about the relationship between physiological data found and certain interaction processes. Therefore, the results of such studies should always be interpreted carefully. For example, the empatica E4 captures the physiological states of arousal but does not distinguish between excitement and distress (Endedijk et al., 2018). Other studies indicate that negative emotions are high and positive emotions are low, but additional validation of these findings is preferable. More research that has explanatory power is required to understand the interplay between metacognition, regulation, physiological signals, and physiological concordance. To understand to what extent physiological processes are aligned and how that influences the dynamics within the team also more research is needed (Endedijk et al., 2018).

Sensor technology is being used more and more but a lack of common methods for computing them was observed in the results. In several studies that were measuring, for example, metacognitive monitoring, different analytical techniques were used (Malmberg et al., 2019; Haataja et al., 2018). The field would benefit from building more standardized procedures across disciplines by sharing, replicating, and moving towards combining different data modalities and analytical techniques (Noroozi et al., 2020). More advanced analysis methods should be applied to investigate these types of data and investigate group processes (Malmberg et al., 2019). A new journal might help understand the analytical techniques used to deal with multimodal process data, a might provide a starting point for the standardization of procedures and tools for this process (Noroozi et al., 2020).

All the results together argue for including multiple process measures in team interaction research. Particularly, physiological data are worth exploring further in terms of increasing the relatively low number of publications. To get a more complete picture of team interaction processes it is encouraged to use multimodal data to research cognitive, motivational, and emotional aspects of interaction together, and not separately. The use of more advanced technologies and tools that facilitate the collection of multiple process measures is recommended. More research that has explanatory power is required to further explore and understand the interplay between different interaction processes.

Practical implications

All the different findings lead eventually to some practical implications. With the use of sensor technologies, teams can be provided with real-time feedback on their interaction processes. Such instant feedback can be used in several ways. As described in Wiltshire et al. (2021) teams can receive instant feedback through visualizations, this may result in increased rates of acceptance and accountability for individual behaviour and thus improve overall team dynamics. It can, for example, also be used to design a model that is capable of automatically detecting students’ metacognitive activity as an indicator for difficulties that arise in collaborative learning (Malmberg et al., 2019). With this information, the students can be helped during these difficult moments. Another example is the use of real-time feedback in a professional team. Information about the underlying interaction processes can also be used in the design of training and education for professionals (Endedijk et al., 2018). With this feedback, the teams can learn to better understand what is required during certain moments of interaction and optimize these interactions (Endedijk et al., 2018).

Limitations & strengths

Several limitations are acknowledged in this review. Firstly, the reviewed studies are all carried out in western Europe. Therefore, multicultural aspects of team interactions are neglected in these types of studies. For example, Yuki et al. (2007) found that there are differences in interpreting the emotional expressions of the other person between Japanese people and Americans. This suggests that some aspects of team interactions, such as interpreting emotional expressions, vary in different cultural contexts (Noroozi et al., 2007).

Secondly, in the studies the samples mostly consisted of students, only one study was done within a professional management team. This points out the need for widening the sample scope of this type of research for more generalizable results.

The limited empirical research on this topic this review relied on is another limitation of this study. Despite the broad literature search, only seven relevant sources were identified. This emphasizes the need for more empirical research with this type of study design, but also the need for more standardized methods to make this type of study design easier to implement. It must also be acknowledged that some studies could have followed a multimodal approach with the use of process measures in the context of teams without using those terms.

Despite the limitations, this study also had some strengths. Firstly, it was, to the author’s knowledge, the first review on the topic of studies using at least two modalities that collect process measures over time in the context of teams. Information about how currently this type of study design is being used in different fields of study was described. These findings contribute to our understanding of the use of multimodality studies that collect process measures.

Conclusion

This research aimed to create an overview of studies using at least two modalities that collect process measures over time in the context of teams. Based on the review of seven empirical studies this overview was created. It creates a foundation on which innovative research and technologies can be developed. It can advance our scientific knowledge of team dynamics by defining constructs from sensor-based metrics and tell us about the strength of this study design. It helps to understand the added values and limitations of combining multiple process measures in a team context. This type of study design has significant potential, however current theories and technologies need to be improved and standardized to make its implementation easier. Much more research and interdisciplinary collaboration are necessary to achieve this.

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Appendix A: Literature search records

Scopus

(Multimodal OR multimodality) AND team → 415

Multimodal* AND sensor → 161

Multimodal* AND sensor AND team → 5

Multimodal* AND sensor AND dynamic* → 18

Brdiczka, O., Maisonnasse, J., Reignier, P., & Crowley, J. L. (2009). Detecting small group activities from multimodal observations. *Applied Intelligence*, *30*(1), 47-57.

Multimodal data AND technology AND team → 4

Martinez-Maldonado, R., Kay, J., Buckingham Shum, S., & Yacef, K. (2019). Collocated collaboration analytics: Principles and dilemmas for mining multimodal interaction data. *Human–Computer Interaction*, *34*(1), 1-50.

Multimodal data AND technology AND interaction → 35

Seedhouse, P., & Almutairi, S. (2009). A holistic approach to task-based interaction. *International Journal of Applied Linguistics*, *19*(3), 311-338.

Multimodal data AND (technology OR sensor) AND (interaction OR dynamic*) → 48

Social sensing AND team → 11

Cook, A., Meyer, B., Gockel, C., & Zill, A. (2019). Adapting leadership perceptions across tasks: micro-origins of informal leadership transitions. *Small Group Research*, *50*(2), 227-265.

Team dynamic* AND physiolog* → 36

Kazi, S., Khaleghzadegan, S., Dinh, J. V., Shelhamer, M. J., Sapirstein, A., Goeddel, L. A., ... & Rosen, M. A. (2021). Team physiological dynamics: A critical review. *Human factors*, *63*(1), 32-65.

Google Scholar

Multimodal* AND team → 366.000

Multimodal* AND sensor → 312.000

Multimodal* AND team AND technology → 150.000

Team AND interaction AND multimodal* AND sensor → 34.300

Team AND dynamics AND technology → 3.160.000

Kozlowski, S. W., & Chao, G. T. (2018). Unpacking team process dynamics and emergent phenomena: Challenges, conceptual advances, and innovative methods. *American Psychologist*, *73*(4), 576.

Team-dynamics AND sensor AND multimodal* AND unobtrusive → 113

Multimodal* data AND objective AND team dynamic* → 77.700

Lechappe, A., Chollet, M., Rigaud, J., & Cao, C. G. (2020, October). Assessment of situation awareness during robotic surgery using multimodal data. In *Companion Publication of the 2020 International Conference on Multimodal Interaction* (pp. 412-416).

Chopade, P., Khan, S. M., Edwards, D., & von Davier, A. (2018, October). Machine learning for efficient assessment and prediction of human performance in collaborative learning environments. In *2018 IEEE International Symposium on Technologies for Homeland Security (HST)* (pp. 1-6). IEEE.

Chopade, P., Edwards, D., Khan, S. M., Andrade, A., & Pu, S. (2019, November). CPSX: Using AI-Machine Learning for Mapping Human-Human Interaction and Measurement of CPS Teamwork Skills. In *2019 IEEE International Symposium on Technologies for Homeland Security (HST)* (pp. 1-6). IEEE.

"multimodal data" AND "team dynamics" → 72

Omurtag, A., Roy, R. N., Dehais, F., Chatty, L., & Garbey, M. (2019). Tracking team mental workload by multimodal measurements in the operating room.

Wiltshire, T. J., Hudson, D., Lijdsman, P., Wever, S., & Atzmueller, M. (2020). Social analytics of team interaction using dynamic complexity heat maps and network visualizations. *arXiv preprint arXiv:2009.04445*.

"multimodal data" AND "nonverbal behaviour" AND "team dynamics" → 23

Niewiadomski, R., Mancini, M., Baur, T., Varni, G., Griffin, H., & Aung, M. S. (2013, October). MMLI: Multimodal multiperson corpus of laughter in interaction. In *International Workshop on Human Behavior Understanding* (pp. 184-195). Springer, Cham.

Sensor technology AND team dynamics → 228.000

Kolbe, M., & Boos, M. (2019). Laborious but elaborate: The benefits of really studying team dynamics. *Frontiers in Psychology*, 1478.

- Source cited in Kolbe & Boos (2019)
  - Schmid Mast, M., Gatica-Perez, D., Frauendorfer, D., Nguyen, L., & Choudhury, T. (2015). Social sensing for psychology: Automated interpersonal behaviour assessment. *Current Directions in Psychological Science*, *24*(2), 154-160.

Wearable sensors AND team interaction → 49.400

Gatica-Perez, D. (2009). Automatic nonverbal analysis of social interaction in small groups: A review. *Image and vision computing*, *27*(12), 1775-1787.

Web of Science

Multimodal AND team → 1.200

- Djordjilovic, O. (2012). Displaying and developing team identity in workplace meetings–a multimodal perspective. *Discourse Studies*, *14*(1), 111-127.
- Hirvonen, M. I., & Tiittula, L. M. (2018). How are translations created? Using multimodal conversation analysis to study a team translation process. *Linguistica Antverpiensia, New Series: Themes in Translation Studies*.
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Multimodal AND team dynamics AND technology → 13

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Multimodal AND team dynamics AND sensor → 8

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Appendix B: Elimination process of irrelevant sources

<table>
<tr><th>Source</th><th>Modalities used</th></tr>
<tr><td>Brdiczka, Maisonnasse, Reignier, & Crowley, (2009)</td><td>2: Speech activity detector & visual tracking system → include?</td></tr>
<tr><td>Martinez-Maldonado, Kay, Buckingham Shum, & Yacef, (2019)</td><td>
<table>
<tr><th>Case & Technology</th><th>Data</th><th>Cohort</th><th>N</th><th>NO.of Groups</th><th>Analytics Techniques</th><th>Devices</th><th>Purpose of the Analytics</th><th>Target Users</th></tr>
<tr><td>1: A multidisplay optimization challenge</td><td>Voice, clickstream, app logs</td><td>Adults</td><td>39</td><td>13 triads</td><td>Prediction & classification</td><td>Vertical displays & pc's</td><td>Predicting collaboration</td><td>Researchers</td></tr>
<tr><td>2: A pen-based tabletop for 'mystery' solving</td><td>Pens, app logs</td><td>Children</td><td>18</td><td>6 triads</td><td>Prediction, clustering & visualization</td><td>Tabletop & pens</td><td>Mining collaborative strategies</td><td>Researchers</td></tr>
<tr><td>3: A multi-ouch tabletop for concept mapping</td><td>Touch, voice, app logs</td><td>Adults</td><td>60</td><td>20 triads</td><td>Sequence and process mining</td><td>Tabletop, kinect & mic array</td><td>Predicting collaboration and differentiating strategies</td><td>Researchers & developers</td></tr>
<tr><td>4: A multi-display, multi-touch classroom</td><td>Touch, classroom logs, mobility, dashboard logs</td><td>Higher education students</td><td>376</td><td>22 classrooms 4 groups each</td><td>Sequence mining, clustering & visualization</td><td>Tabletops, vertical displays, tablets, kinects & mic arrays</td><td>Enhancing awareness and feedback</td><td>Facilitators</td></tr>
<tr><td>5: An educational design studio</td><td>Human observations, mobility, tools usage</td><td>Designers & teachers</td><td>20</td><td>4 dyads and 4 triads</td><td>Visualization</td><td>Tabletop, interactive whiteboard, dashboard, tablets, pc & physical objects</td><td>Providing instant feedback</td><td>Collaborators</td></tr>
<tr><td>6: A health-care simulation classroom</td><td>Mobility, voice, manikin logs, simulation status, self-reports</td><td>Health students</td><td>56</td><td>11 groups of 5-10 medical trainees</td><td>Exploration</td><td>Medical manikins & sensors</td><td>Providing delayed feedback</td><td>Collaborators</td></tr>
</table>
Is this useful or exclude?</td></tr>
<tr><td>Seedhouse, & Almutairi, (2009)</td><td>3: Task-tracking hardware & software, video/audio recording, and transcription → include</td></tr>
<tr><td>Kazi, Khaleghzadegan, Dinh, Shelhamer,</td><td>Exclude→ literature review</td></tr>
</table>

Sapirstein, Goeddel, & Rosen, (2021)	
Kozlowski, & Chao, (2018)	→ Exclude
Lechappe, Chollet, Rigaud, & Cao, (2020, October).	5: Questionnaires, empatica E4 sensor, 2 fixed cameras, 2 microphones, recorded surgical view → include
Chopade, Khan, Edwards, & von Davier, (2018, October)	System to analyse data→ Exclude
Chopade, P., Edwards, D., Khan, S. M., Andrade, A., & Pu, S. (2019, November)	Room:Camera, microphone, speakerphone, scratch paper Game: game logs, chat logs, eyetracking with screen capture, portrait videos, audio files
Kolbe, M., & Boos, M. (2019).	Focus on literature → exclude
Schmid Mast, Gatica-Perez, Frauendorfer, Nguyen, & Choudhury, (2015)	Current techs used → exclude

Gatica-Perez, (2009)	A review→ exclude
Djordjilovic, (2012)	Video-recorded meetings; only 1 modality→ exclude
Hirvonen, & Tiittula, (2018)	Video → exclude
Neubauer, C., Woolley, J., Khooshabeh, P., & Scherer, S. (2016, October)	4: Questionnaire, video of facial expression, microphone, heart rate variability → include
Spikol, D., Ruffaldi, E., Landolfi, L., & Cukurova, M. (2017, July)	3: Frontal camera, top down camera, audio, information about the types of physical and software blocks used in the project → include
Kim, T., McFee, E., Olguin, D. O., Waber, B., & Pentland, A. S. (2012)	Case studies can be useful? → speech, interaction & body movement patterns, location
Chaffin, Daniel, Ralph Heidl, John R. Hollenbeck, Michael Howe, Andrew Yu, Clay Voorhees, and	review→ exclude

Roger Calantone (2017)	
Kayhan, V. O., Chen, Z. C., French, K. A., Allen, T. D., Salomon, K., & Watkins, A. (2018).	Protocol → exclude
Bhattacharya, I. (2019).	Book → exclude
Endedijk, M., Hoogeboom, M., Groenier, M., de Laat, S., & Van Sas, J. (2018)	3: Speech (microphone) video, empatica E4 (skin conductance) → include
Cook, A., Meyer, B., Gockel, C., & Zill, A. (2019).	3: Sociometric badge (mic, Bluetooth, infrared), camera → include
Omurtag, A., Roy, R. N., Dehais, F., Chatty, L., & Garbey, M. (2019).	5:data from EEG, heart rate and breathing rate, tool handle pressure, and eye tracker → include

Wiltshire, T. J., Hudson, D., Lijdsman, P., Wever, S., & Atzmueller, M. (2020).	sensor-based social analytics of Sociometric badges (Rhythm Badge) with two visualization techniques (Dynamic Complexity Heat Maps and Network Visualizations)
Niewiadomski, R., Mancini, M., Baur, T., Varni, G., Griffin, H., & Aung, M. S. (2013, October)	3D body position information, facial tracking, multiple audio, and video channels as well as physiological data