“Who Knows What”? An interdisciplinary approach to investigate the Transactive Memory System

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Prologue

In this chapter, we focus on a particular team’s emergent state, called the Transactive Memory System (TMS). This phenomenon refers to the shared mental representation of how knowledge is distributed among team members performing a task. More details about the theoretical background and previous research on TMS are described below. In the work presented in this chapter, we were interested in better understanding the behavioral dynamics related to TMS to improve the automated estimation of TMS from the team’s non-verbal behaviors. These results could guide, in turn, the design of human-centered computing applications to help team interactions.

What you need to know about the Transactive Memory System

When interacting in a team, at the individual level, people exploit their transactive memory, a meta-memory determining one’s field of knowledge. At the team level, through interaction and communication, each member becomes aware of the knowledge and skills of the others. Individual transactive memory combined with the communication processes that occur within the team allows the development of the Transactive Memory System (Wegner, 1987). A mental representation of “who knows what” enables them to plan “who will do what”, resulting in more efficient individual and collective performance (Gupta & Hollingshead, 2010).

Theoretical background of TMS. While initially studied in the context of intimate couples (Wegner, 1987), more recent studies investigated TMS in teams of three or more people (for a review, see (Peltokorpi, 2008; Ren & Argote, 2011)).

A TMS develops in teams working on interdependent tasks (i.e., the members need to interact to complete the task) requiring different types of expertise. Indeed, if team members alone could accomplish the task, there would be no need for them to build a cognitive map of others’ knowledge. This point highlights a fundamental condition for a well-functioning TMS, that is, knowledge differentiation: the extent to which team members are experts in areas that other members are not (Wegner, 1987). This specialization reduces individuals’ cognitive effort. In turn, knowledge differentiation can only be effective when the team members accurately identify the others’ expertise (Faraj & Sproull, 2000), accept these specializations, and trust them. In this way, the team can work in a coordinated and efficient way.

These dynamics were formalized by Moreland (R. L. Moreland & Myaskovsky, 2000) and Lewis (Lewis, 2003) who defined the three dimensions of TMS: (i) Specialization of members’ knowledge: the extent to which team members are experts in areas that other members are not; (ii) Credibility: the belief about the reliability of other members’ knowledge; (iii) Coordination: an effective, orchestrated knowledge processing.

A well-developed TMS can significantly improve team performance and productivity (Austin, 2003; Kozlowski & Ilgen, 2006; Lewis, 2003; R. Moreland, 1999; R. L. Moreland & Myaskovsky, 2000) as well as reduce individual cognitive load (Hollingshead, 2000).

TMS is a memory system, and like other memory systems, it develops in three stages: encoding, storage, and retrieval. The *encoding* stage is considered an input for the individual: each team member can learn “who knows what” through interpersonal interactions. During the *storage* stage, the information is allocated to members with matching expertise (Liao, Jimmieson, O’Brien, & Restubog, 2012). During the *retrieval* phase, the team members can access the needed resources if they are aware of the knowledge distribution in the team.

How to measure TMS. Compared to behavioral or affective emergent states such as cohesion, trust, or decision-making (Lewis & Herndon, 2011; Liang, Moreland, & Argote, 1995; R. L. Moreland & Thompson, 2006), TMS refers to a more abstract cognitive process. This makes it more challenging to measure explicitly. Some indicators of TMS used in previous studies include team performance as well as external and self-assessment of TMS. In particular, the most used questionnaire is the one from Lewis (2003), which measures the three dimensions *Specialization*, *Credibility* and *Coordination*.

Given the critical role of interpersonal communication in TMS development (Peltokorpi & Hood, 2019), an alternative method to assess TMS in a team is to analyze the non-verbal behaviors during the interaction between the members. Spatial arrangement, proxemics, and turn-taking behaviors have been found to play a role in the development of emergent states such as cohesion (Hung & Gatica-Perez, 2010; Walocha, Maman, Chetouani, & Varni, 2020) and leadership (Sanchez-Cortes, Aran, Mast, & Gatica-Perez, 2011). Similar patterns could be related to TMS.

Do not change a winning team

This chapter is a perfect example of the benefits of a well-developed TMS in teamwork, i.e., those that involved the chapter’s authors. Before working on the project described in this chapter, we had previously collaborated on several projects, but not on the topic of team analysis. Interestingly, the key ingredients for our successful collaboration reflect the three TMS dimensions, i.e., *Specialization*, *Credibility* and *Coordination*.

First, *Specialization* was well represented in the background and expertise of the authors:

- Beatrice Biancardi, Associate Professor at CESI (Centre des Etudes Supérieures Industrielles) LINEACT (Laboratoire d’Innovation Numérique pour les Entreprises et les Apprentissages au service de la Compétitivité des Territoires), France, has a background in Cognitive Science and Human-Computer Interaction (HCI). She works on HCI inspired by socio-cognitive theories, focusing on non-verbal behavior modeling. Her main contribution to the current work was to apply theoretical psychological models of TMS to the design of experimental protocols for the automated analysis of TMS.
- Maurizio Mancini, Associate Professor at Sapienza University of Rome, Italy, has a

background in Computer Science. He has expertise in Feature Engineering and Data Science. His contribution to the current work was to develop non-invasive sensors and implement algorithms for the automated analysis of the team’s non-verbal behavior.

- Giovanna Varni, Associate Professor at DISI (Dipartimento di Ingegneria e Scienza dell’Informazione), University of Trento, Italy, has a background in Engineering. She has previous experience in automated group analysis and human-centered computing. Her main contribution to the current work was to apply her previous experience on emergent states and group analysis to investigate TMS.

Specialization is not helpful to developing TMS without mutual trustworthiness between the team members: the *Credibility* dimension. The mutual trustworthiness between us, developed during previous collaborations, made us open to applying each other’s different approaches and methodologies in our research. In the following sections, several examples will be provided of how merging our distinct expertise in Computer Science and Social Science was beneficial to investigating TMS. Finally, the mutual trustworthiness facilitated fluid interactions in our team, as well as high *Coordination* during the research work, resulting in several achievements presented in this chapter.

What this chapter is not

The purpose of this chapter is to highlight the benefits and drawbacks of an interdisciplinary approach to tackling challenges from both Computer Science and Social Science when studying teams, with a focus on the Transactive Memory System. We will not provide a review of the theoretical frameworks nor previous work on TMS. For this, we recommend the work from (Ren & Argote, 2011), and broader reviews on team cognition (DeChurch & Mesmer-Magnus, 2010; Mohammed, Rico, & Alipour, 2021). Instead, our contribution is to leverage our personal experience to provide insights and guidelines for the community and facilitate future interdisciplinary research.

Interdisciplinary Collaboration and the Research

Main goal

As previously introduced, our research focuses on TMS, one of the less-studied emergent states. Our long-term goal is to contribute to investigate the following issues: *How to develop human-centered applications to monitor TMS and improve teams' performance and affective outcomes on collaborative tasks?*

Like for other emergent states (e.g., leadership and cohesion), we assumed that a human-centered application could monitor TMS status by looking at teams' non-verbal behaviors. Therefore, the first step of our interdisciplinary approach was to investigate the relationship between non-verbal features and TMS. Next, we compared the efficacy of different interventions of a human-centered application (in our case, a socially interactive agent (Lugrin, 2021)) to facilitate the development of the team's TMS.

Disciplines Involved. Our journey into TMS involved several disciplines, from Computer Science and Social Science. These included Feature Engineering, Data Science, Computational Modeling, Cognitive Science, and Psychology.

The main achievements described in the following section were realized thanks to collaborations with other researchers: Brian Ravenet, Associate Professor of Computer Science at Paris-Saclay University, France, who participated in all achievements; Lou Maisonnave-Couterou and Pierrick Renault, Master students in Psychology from University Paris Cité, who collaborated on Achievement 1; Enzo Tartaglione, Associate Professor of Deep Learning at Télécom Paris, France, who collaborated on the first part of Achievement 2; Ivan Giaccaglia, Master student in HCI from University of Trento, Italy, and Patrick O'Toole, PhD student in Computer Science from University College Cork, ireland, who collaborated on Achievement 3.

The following sections will illustrate how these researchers with different backgrounds and expertise successfully contributed to the same goal: a better understanding of TMS.

Main achievements

Achievement 1: A new dataset. As soon as we started our work, we were confronted with a practical requirement: to investigate human interactions, we need data. Although several datasets of team dynamics were available, none of them collected measures of TMS. We thus decided to collect a new dataset and focused on the following research question:

RQ1: What experimental setting could allow us to observe and measure the emergence and development of TMS in small teams while maximizing natural interactions?

This led to our first contribution: the WoNoWa dataset (Biancardi et al., 2020). To date, it is still the unique dataset directly addressing the study of TMS in small teams (a summary of small teams interaction datasets can be found in (Beyan, Vinciarelli, & Bue, 2023)). The WoNoWa dataset includes a rich set of extracted multi-modal features, manual annotations of non-verbal behaviors, and participants’ self-assessments of the three dimensions of TMS, for 15 teams of three members. The recording setup of the WoNoWa dataset was conceived to minimize invasive sensors and facilitate naturalistic interactions between the team members. Only two video cameras (plus a third one for manual annotation) and wireless microphone headsets were used. The automated tracking of the participants’ position and movements was ensured thanks to colored t-shirts and unique ArUCc markers (Garrido-Jurado, Muñoz-Salinas, Madrid-Cuevas, & Marín-Jiménez, 2014) positioned on the participants’ caps and on the floor. ArUco markers are 2D barcode-like patterns (fiducial markers) which have been heavily used in robotics, augmented reality and computer vision for identifying and locating objects.

The design of the WoNoWa dataset is firmly based on the theoretical framework of TMS we introduced in the previous section: the three memory phases *encoding*, *storage*, and *retrieval* were reproduced in the protocol to facilitate TMS emergence. The participants were grouped in teams of three. They first had to choose one distinct field of expertise per participant, from logistical, mathematical, and manual expertise. Then, each of them developed their expertise by watching the corresponding tutorial. More specifically, the tutorials were about setting up the table by following specific rules (logistical), the Imperial measurement system (mathematical), and making a heart and a frog origami (manual). Finally, they were asked to accomplish several tasks requiring all the learned expertise. In addition, the tasks performed by the teams during the *retrieval* phase were designed to elicit and develop TMS by proposing different types of collaboration. This manipulation was successful, as shown by the high scores of *Specialization*, *Coordination* and *Credibility* reported by participants through questionnaires (Lewis, 2003) filled out at the end of each task. In particular, an increase of *Credibility* was measured across the different tasks (Biancardi et al., 2020).

The WoNoWa dataset is thought to be a resource for developing computational models of TMS to predict and enhance team collaboration. The rich set of features can be exploited by different communities of researchers focusing on several aspects of team interactions. More interestingly, most of the features can be easily computed in real-time, thus the knowledge provided by the analysis of the WoNoWa dataset could be applied to the development of human-centered applications to monitor teams’ TMS and give real-time feedback when needed.

Achievement 2: Modeling TMS from non-verbal behavior. Thanks to the WoNoWa dataset, it was now possible to investigate our second research question:

RQ2: What behavioral patterns could be used to predict the level of TMS of a team?

In particular, we were interested in which uni-modal and multi-modal behaviors characterize the three dimensions of TMS. Our analyses focused on the task with the highest values of TMS (i.e., the third step of the *Retrieval* phase), where the team members needed knowledge of the others’ expertise to accomplish the task. The high development of TMS during this step was confirmed by higher scores of *Credibility* compared to the previous tasks, as well as high scores of *Specialization* and *Coordination.*

The feature set included three categories: audio, movement, and spatial features. The first two categories were automatically annotated, while the latter was manually annotated. Audio features were related to vocal turn-taking including, for example, the average speaking turn duration or the number of successful interruptions. Movement features were computed from head position and rotation tracked through the ArUco markers on the participant’s caps, and the silhouette blobs were extracted through color thresholding thanks to the colored t-shirts worn by the participants. Spatial features related to participants’ arrangement in the interaction space, including f-formations (i.e., spatial arrangements made by the team members oriented towards the same object of attention (Kendon, 1990)) and task-related area occupation (i.e., personal, others, or common area). Most features were initially computed for each team member and then merged to obtain team features.

We explored different approaches to predict TMS dimensions (i.e., *Specialization*, *Credibility*, and *Coordination*) from non-verbal features. We performed a preliminary analysis to compare traditional Machine Learning approaches based on Feature Engineering (Decision Trees and Logistic Regression) with fully automated deep learning approaches such as Artificial Neural Networks (Convolutional Neural Network and Multi-Layer Perceptron). The extracted features from WoNoWa dataset were processed by applying features normalization, dimensionality reduction (through Principal Component Analysis) and data augmentation. More details can be found in (Tartaglione, Biancardi, Mancini, & Varni, 2021). In the context of the analysis of team dynamics, available datasets (including WoNoWa) are often small, making a model’s training more delicate and complex than other scenarios, such as image classification. Despite their high potentiality of learning complex non-linear relationships between data, Deep Learning approaches are highly prone to overfit data. When dealing with small datasets without a proper prior knowledge base, their hyper-parameters are extremely hard to optimize. Our results confirmed this, showing poor performance of Deep Learning approaches while Decision Trees provided the best results. This highlights the importance of a prior knowledge base applied to Feature Engineering, which cannot be learned and optimized by Deep Learning approaches from a small dataset such as WoNoWa (15 groups).

This first study confirmed that Deep Learning approaches were not the best choice in our case, and more “white box”, or transaparent, models should be favored. This was in line with our goal to use models’ output to produce feedback for the team, as the advantage of such models is to achieve high-performance scores while maintaining the readability of the models simultaneously.

Multiple regression analysis was thus chosen to model the three TMS dimensions, as it would facilitate meaningful interpretation of the relationship between non-verbal features and *Specialization*, *Credibility*, and *Coordination*. Regression models were run with data extracted from 1 to 3 modalities alone or merged together (i.e., data from audio, movement, spatial only, or data from two modalities as well as data from all the three modalities together) and, at most, four features (due to the small number of teams compared to the number of features). The best models (i.e., those having the highest R^2 score) from all the significant ones (i.e., those having a p-value < 0.05 for every feature) were selected. A complete description of this work can be found in (Biancardi, Mancini, Ravenet, & Varni, 2024). Results showed that, in general, better performance (i.e., highest R^2) could be obtained by multi-modal models (i.e., combining audio, movement and spatial features), compared to uni-modal and bi-modal models, keeping the same number of features. Similar to previous work on automated analysis of team emergent states, turn-taking features were confirmed to be good estimators of the TMS.

The total number of speaking turns per minute, for example, was found to be a negative predictor of *Credibility* and *Coordination*, while the average speaking turn duration positively predicted *Coordination*. Features related to the spatial arrangements were also good estimators of the TMS dimensions. For example, high specialized teams, the members tended to arrange in the space by following triangular configurations. In addition, for high values of *Specialization*, the team members’ movements continuously varied following non-linear trajectories. For high *Coordination* scores, the members tended to stay close to each other and performed activities related to the coordination of the tasks (by working in the common area).

Achievement 3: Virtual leaders influencing TMS. The work presented in the previous section showed that it is possible to automatically detect the level of TMS in a team from non-verbal behaviors. The next step towards enabling human-centered applications to help human teams in real-time is to understand how these applications can intervene once an issue in team collaboration is detected. In particular, we focused on the role of Social Interactive Agents (SIA) (Lugrin, 2021), i.e., autonomous agents capable of interacting in a socially intelligent manner using multi-modal communicative behaviors. Previous work showed that agents’ anthropomorphism and their ability to adhere to social norms make it easier for them to be accepted as teammates by human users (Seeber et al., 2020; Złotowski, Proudfoot, Yogeeswaran, & Bartneck, 2015). We thus addressed SIA in the form of computer interfaces displaying a human-like embodiment (i.e., Embodied Conversational Agents). In addition, previous studies in human-human interaction showed that leaders can use TMS to encourage interactions by establishing connections and translating different knowledge structures over different functions (Soekijad, van den Hooff, Agterberg, & Huysman, 2011). Leader interventions are also often linked to coordination by providing explicit cues for expertise and motivating team members to accept specific duties and roles (Larson Jr, Foster-Fishman, & Franz, 1998). Therefore, we decided to investigate the role of SIA as virtual leaders. In human-agent interaction, the impact of virtual leaders has been studied in the context of team collaboration (Hayashi, 2012; Jackson, Bevacqua, Loor, & Querrec, 2019), but not in relation to TMS. Our research question was the following:

RQ3: How to design virtual leaders encouraging the development of a team’s TMS?

Two leadership styles are positively associated with the development of TMS: Transformational Leadership (TFL) and Transactional Leadership (TAL) (Bachrach &

Mullins, 2019). The first is based on providing inspiration, faith, and respect to the followers; the second is based on contingent rewards or punishments (Brymer & Gray, 2006). TFL has a more supportive and cooperative approach, focusing on the intrinsic values of the team, compared to TAL, which is characterized by more directive and dominant behaviors, intensifying the extrinsic values of the team (Jung & Avolio, 2000). Based on the literature in human-human interaction, we identified non-verbal behaviors specific to each of the two leadership styles (Awamleh & Gardner, 1997; Fradet, 13; Imai, 1996; Kendon, 2000; Schyns & Mohr, 2004). For TFL, Awamleh and Gardner identified several key non-verbal behaviors: maintaining eye contact, speaking fluently without hesitation, displaying expressive facial cues (such as smiling), and using dynamic hand and body movements (Awamleh & Gardner, 1997). Similarly, Schyns and Mohr highlighted additional behaviors commonly associated with TFL leaders, including alternating between pacing and sitting on the edge of a desk, leaning in toward the audience, and exhibiting a wide range of expressive facial gestures (Schyns & Mohr, 2004). In contrast, the literature offers less clarity regarding non-verbal behaviors specific to TAL. Nonetheless, drawing from research on dominant nonverbal behavior—aligned with the authoritative and directive nature of TAL—some patterns can be inferred (Burgoon & Dunbar, 2006). Dominant individuals are often observed using downward palm gestures, which may signal disapproval or assert power (Imai, 1996; Kendon, 2000). They also tend to adopt closed, commanding postures, such as crossing their arms, and maintain more neutral facial expressions.

To answer our research question, we conceived and conducted an experimental study where we investigated how a virtual leader intervention is perceived to impact a team’s TMS. This work was realized during the pandemic; thus, it was adapted as an online perceptive study. Each participant watched three video clips of a team acting in a design thinking scenario (Pusca & Northwood, 2018). This particular scenario was chosen because it is related to leadership styles and TMS: TFL and TAL are supportive to design thinking and useful to explain its benefits (Schweitzer, 2014). The team members exhibited distinct expertise and, in each video, they emphasized difficulties in one of the three TMS dimensions. After each clip of the team, the participants watched video clips showing an intervention by the virtual leader using TFL or TAL style expressed using a sentence and the corresponding non-verbal behavior. *Specialization*, *Credibility* and *Coordination* of the team were assessed by participants after each team interaction. In addition, after watching each virtual leader intervention, they were asked to hypothesize how the behavior of the leader could affect the future behavior of the team (on the same three TMS dimensions). To compare the impact of a virtual leader with a human one, two groups were involved in the study. The first assessed the virtual leader intervention, while the second group followed the same experimental design, but a human actor replaced the agent, performing the same behaviors. The independent variables manipulated were:

- *Activity*, understood as the three team activities, each emphasizing difficulties in one of the three TMS dimensions, with levels: “Division of Work” (*Division*), “Sharing Ideas” (*Sharing*) and “Choosing an Idea” (*Choosing*);
- *Intervention*, understood as the type of intervention, if present, of the team leader, with levels: *Before*, *TFL*, *TAL*;
- *Leader Embodiment*, understood as the leadership type, with levels: *Agent*, *Human*.

A total of 60 participants took part in the study: 28 in the *Agent* and 32 in the *Human* condition. More details can be found in (Biancardi, Giaccaglia, Ravenet, & Varni, 2021; Biancardi, O’Toole, et al., 2021).

Except for *Division* activity, results showed a general positive impact of the intervention of both the virtual and human leader on the perceived TMS of the team. TMS scores given for *Before* level of *Intervention* variable were lower than those given after both *TFL* and *TAL*. No main effect of *Leader Embodiment* was found, while an interaction between *Leader Embodiment* and *Intervention* was statistically significant. In particular, *TFL* style worked better than *TAL* when performed by a human, while both *TFL* and *TAL* styles equally improved TMS perception (compared to the *Before* condition) when performed by a virtual leader. This highlights the potential of virtual leaders to positively affect a team’s TMS when performing any leadership style.

These results are promising since they support the use of Socially Interactive Agents in human-centered applications as effective team leaders, capable of engaging teams of users and supporting them in developing complex cognitive phenomena, such as TMS. These results provide promising first insights, but future work is needed to evaluate the impact of a virtual leader in a real-time interactive scenario with a team.

How the interdisciplinary approach won

The main achievements presented above were obtained thanks to the collaboration of several researchers from a large set of disciplines. When the benefits of one discipline allowed us to face the drawbacks of another, the interdisciplinary approach won. Below, we identify the main contributions that could not have been realized using a Computer Science-only or Social Science-only approach.

First of all, psychological theories were crucial to the design of the experimental studies. For Achievement 1, a challenge of the laboratory setting was to elicit the emergence of TMS in a relatively short time. The cognitive science framework characterizing TMS as the result of three memory phases (i.e., *encoding*, *storage*, and *retrieval*) was applied to the protocol to optimize the emergence of TMS. Similarly, the tasks realized by the team members were designed to represent the three TMS dimensions extensively studied in the literature. This scientific background allowed our protocol to elicit TMS successfully and provided the basis for the automated analysis of the phenomenon. On the other hand, data collection would not have been possible without the technical setup we realized, which ensured the proper recording of participants’ behaviors while minimizing the intrusiveness of sensors. Previous expertise in the automated analysis of team emergent states, as well as Computer Science and Data Science, guided the choice of a simple setup where only two cameras and ArUco markers, well positioned in the room, were enough to produce exploitable data for the feature extraction. This expertise allowed us to go beyond classical studies on TMS in Psychology, mainly based on observation, allowing for a more fine-grained automated analysis of the interaction. For Achievement 3, we relied on Psychology literature on leadership and studies of human-human interaction to identify the two leadership styles and select the corresponding behaviors of the virtual leader. Expertise from HCI was needed to implement these behaviors. Still, it also proved to be helpful in the design of the protocol, in particular in the choice of the task realized by the participants. Design thinking is an approach used in HCI and was particularly appropriate for our study. Indeed, design thinking is characterized by collaborative tasks requiring different expertise and has been found to be related to leadership and TMS.

The interdisciplinary approach also succeeded during the Feature Engineering work realized for Achievements 1 and 2. Technical expertise was needed to process raw data from the cameras and microphones. Audacity[1] was used to process raw audio files. At the same time, head positions and rotations from ArUco markers and silhouettes from colored t-shirts were extracted using the OpenCV library (Bradski, 2000). From this data, a huge set of possible features could be extracted. Expertise in team analysis and knowledge from previous work in Psychology allowed us to select appropriate features. Many of them were already used in previous work on emergent states (e.g., turn-taking, vocal features (Hung & Gatica-Perez, 2010; Sanchez-Cortes et al., 2011)), and social interaction (Bresin, Mancini, Elblaus, & Frid, 2020; Frid, Bresin, Alborno, & Elblaus, 2016; Varni & Mancini, 2020). Other features were manually annotated following a classical approach from Psychology, and were inspired by previous work on non-verbal behavior (e.g., (Burgoon, Guerrero, & Manusov, 2016; Tong, Serna, Pageaud, George, & Tabard, 2016; Zhang & Hung, 2016). Combining both automated and manual annotations allowed for a richer and

[1] `https://www.audacityteam.org`

more relevant feature set. Regarding the annotation of f-formations, while algorithms exist for their automated detection (Setti, Russell, Bassetti, & Cristani, 2015), manual annotation was preferred to minimize errors and obtain more accurate data.

Finally, the approaches from Data Science and Social Science were combined during the analysis. From the perspective of Social Science, our goal was to better understand the relationship between non-verbal behavior and TMS dimensions. Thus, we were leaning towards running simple and explainable models. Data Science allowed us to reinforce the choice of such models, showing that for the specific dataset type we were dealing with (i.e., a relatively small quantity of data), complex models such as artificial neural networks were not the best choice, while more straightforward and interpretable models were to favor.

Lessons Learned

To reach the achievements detailed above, we faced several challenges that typically occur when studying TMS. These include, among others, eliciting TMS emergence in a laboratory setting as well as modeling such an abstract emergent state as a linear combination of non-verbal multi-modal features. We also faced other challenges related to the study of team dynamics in general, such as combining approaches from several disciplines.

Below, we share the most relevant lessons we learned. Some of them are thought to help future work on TMS, while others are more general and concerned with the approaches to studying team dynamics. These elements are present in the literature, and our contribution strengthens their relevance by providing additional evidence from our specific study context.

Transactive Memory System is time-related

Challenge. Working on Achievement 1 highlighted the importance of time in TMS development. As discussed at the beginning of this chapter, TMS is a memory system whose development requires several phases (i.e., encoding, storing, retrieval). The affective, behavioral, and performance outcomes of TMS are more probable to occur (and easier to measure) at the end of this memory process, i.e., during the retrieval phase (Ren & Argote, 2011). We tried to reproduce the three steps in our data collection protocol to observe the emergence of TMS within teamwork, even if we are aware that the delay between the three phases remains short. Team members need time to know each other and be aware of each other expertise, and this may require more extended periods. This was a challenge for the full development of TMS and could have limited its analysis.

Possible solutions. Recruiting teams whose members already know each other could maximize the chances for the team to have a well-developed TMS. Still, it would reduce the control of the experimenter on the first steps of the interaction. That is, it would not be possible to observe the conditions in which the team developed directly. However, some detailed information could still be collected a-posteriori using questionnaires and/or well-thought-out interviews. A more costly alternative would be to conduct longitudinal studies, which would allow us to follow a group from the very beginning of their interaction and observe the emergence of TMS. In this case, a potential risk would be the low control of the team interactions between experimental sessions. Sharing additional experiences in real life could reinforce other team emergent states, such as cohesion, which in turn could positively affect TMS. Questionnaires could be used to monitor the team activity between the sessions. Despite their cost in terms of time and resources, we believe that multiple interaction sessions may help reinforce the identification of “who knows what” in a team. The effect of time on TMS development is still understudied (e.g., Lewis (2004); Mo and Xie (2010)). As identified by Zhou and Pazos (2020) in their meta-analysis, a longitudinal study of TMS is an interesting future research direction to provide insights into its evolution.

Challenge. Our work was based on average measures. That is, team members’ self-assessment of TMS was collected at the end of the tasks, and the behavioral measures were aggregated on one score for each feature (i.e., one score per feature per task). This approach was good as a first investigation of the phenomenon but may miss important information on how the behaviors evolved over time and how the team’s perception may vary according to specific behavioral patterns occurring within thin time windows.

Possible solutions. Future work requires investigating temporal-related measures during the different phases of TMS, but also dynamically at a lower level considering thinner time windows. This approach would allow an interactive system to trigger automated feedback as soon as a behavioral pattern related to low TMS is detected instead of at the end of a pre-defined interaction period.

We believe that the challenges and solutions presented above are not TMS-specific and are transferable to the study of other team dynamics.

Different methods for different purposes

Challenge. Working in an interdisciplinary team made us rapidly realize the differences between our approaches. To simplify, we use the same categories mentioned before: Social Science (mainly Psychology) and Computer Science. We will focus here on one challenge that we positively exploited to enrich our work: the different annotation methodologies. Annotation in Social Science is mainly a qualitative process that aims to better understand a phenomenon and discover insights. Traditional approaches involve manual annotation, which can be very expensive in time and energy. Manual annotation of a few minutes could require several hours, as raters must watch and re-watch the same video extract to code different dimensions. Raters are often experts, and they refer to specific observation grids. Usually, the number of annotated samples is narrow but enough to conduct a rich qualitative analysis. On the other hand, the concept of annotations in Computer Science, and more specifically in Machine Learning approaches, includes both automated processing of content (i.e., feature extraction) and data labeling. Automatic feature extraction is an objective process and more reliable than manual annotation. It is useful for annotating fine-grained behaviors like facial expressions and eye gaze, which are hard to annotate manually. However, it can suffer from bias (related, for example, to the choice of formulas) and computational errors. Data labeling involves raters often recruited in large quantities through crowd-sourcing platforms. This can be a suitable method when the task is simple, such as image classification, but less appropriate when the task requires judging more complex phenomena like team dynamics. Another issue concerning automated feature extraction and data labeling relates to unitizing (Reis & Judd, 2000), i.e., segmenting the content into smaller portions before annotation or labeling. Unitizing has been found to affect the annotation of team dynamics such as cohesion (Ceccaldi et al., 2019). In addition, automated annotation often analyzes team behavior as the result of its member's individual behaviors, without considering the team as an entity itself (Maman, 2022).

Possible solutions. What we learned is that there is not a best or worst approach. It is essential for researchers from different disciplines who are working on team dynamics to identify how the strengths of each approach complement each other. So, the solution is TMS! What we suggest is to design an automated annotation process using models from Social Science, to rely on automated annotation when the computational error is known to be minimal, and to keep manual annotation for more complex processes. In future work, it would be interesting to exploit existing workflows proposed by (Baur et al., 2020; Schiller, Hallmen, Don, André, & Baur, 2024). Baur et al. (2020) apply semi-supervised machine learning techniques already during the annotation process by giving the possibility to pre-label data automatically, and integrate the annotation interface with explainable AI visualization techniques. Schiller et al. (2024) introduce DISCOVER, a modular user-friendly software framework specifically developed to streamline computational-driven data exploration for human behavior analysis. Both tools allow for automating the human annotation process through a human-in-the-loop approach. In the future, it would be interesting to investigate whether knowledge of complex high-level annotations of team dynamics can be transferred to an automated approach.

You need more than interdisciplinarity

The main lesson learned from our experience is how to leverage the benefits from both Computer Science and Social Science approaches to facilitate and enrich the study of team dynamics. It is worth noting that this interdisciplinary approach is necessary but not sufficient. Additional knowledge and expertise beyond these two fields are required when dealing with data collection of social interactions. In particular, it is crucial for researchers involved in such tasks to master ethics and data privacy regulations (e.g., GDPR[2] or DPF[3]).

Final Takeaway

To conclude, we can summarize our discussion as follows: Computer Science is a tool to analyze teams, and Psychology is a tool to make sense of this analysis. Studying TMS and, more generally, team dynamics cannot be possible without the close collaboration among researchers from different fields with complementary expertise. Technical skills are crucial to realize the set-up, maximize the efficiency of data collection, and minimize the invasiveness of sensors; theoretical knowledge is critical to the design of the protocol to elicit the emergence of the phenomenon of interest and to select the appropriate features to analyze; additional expertise about ethical and legal issues is a requirement for both sides.

[2] https://gdpr-info.eu/

[3] https://www.dataprivacyframework.gov/s/

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