Chapter 9
Investigating Interaction Dynamics: A Temporal Approach to Team Learning

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Abstract Teams are at the core of every organisation, composed of individuals who continuously collaborate, exchange knowledge and ideas, and constantly learn from one another through formal or informal learning experiences. Team learning is therefore a continuously changing phenomenon that develops and evolves over time as teams interact. In this chapter, we aim to promote the investigation of team learning as a temporal phenomenon, and suggest that its temporality can be captured through team interaction dynamics, defined as continuously changing patterns of micro-behaviours that emerge and evolve as teams operate. We set three key steps for initiating and leading research that captures temporality: (a) identifying the interaction dynamics of interest, (b) figuring out the best way to collect and code these, and finally (c) choosing an analysis technique that helps capture continuously and sequentially unfolding patterns. We offer some 'food for thought' on interaction dynamics that relate to team learning and the added value of investigating them, and present some existing data collection and coding methods. We finally propose a framework for choosing an appropriate analysis technique based on the dynamic output that each analysis generates.

Keywords Team learning · Temporal phenomenon · Interaction dynamics · Patterns · Analysis techniques · Emergent states

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9.1 Introduction

Learning does not occur solely during the short period of attending school and other formal educational programs, but becomes a life-long process, needed to keep up with the rapid development and transformation of the world around us (Heaphy et al., 2018). Organizational structures become increasingly interconnected in complex and oftentimes unfamiliar ways (e.g. incorporation of remote teamwork in almost every workspace due to Covid-19), and individuals are called to learn from one another by experimenting and exchanging experiences and knowledge, while also constantly giving and receiving feedback from each other (Grant & Ashford, 2008; Van de Wiel et al., 2011). Consequently, teamwork becomes a continuous learning experience, a 'phenomenon' unfolding over time, which, as any temporal phenomenon (Roe, 2008), unravels through the implicit or explicit exchange of information as team members collaborate and solve problems together. This phenomenon of team learning through interaction has been strongly associated with innovation and performance in the workspace (Baker et al., 2006; Fay et al., 2015; Gambi do Nascimento et al., 2020).

Various concepts related to team learning, such as information exchange, help-giving and -seeking, and feedback-giving and -seeking have been associated with team performance (Gerken et al., 2016; Van der Rijt et al., 2013). However, while these concepts suggest a dynamic exchange of information, they are mostly studied and represented in static ways, through surveys, interviews, and other retrospective, self-reported data (Onnela et al., 2014). These methods not only lack objectivity and are prone to self-biases when it comes to measuring concepts such as the aforementioned, but are also limited in capturing the dynamic nature underlying team learning interaction processes.

Having conceptualized team learning as a process that takes place during interaction and over time, necessitates the investigation of how professionals actively construct, develop, and transform their interpersonal relationships throughout collaboration (Heaphy et al., 2018; Tynjälä, 2008). In other words, treating team learning as a temporal phenomenon calls for methods to grasp and analyse the continuously unfolding dynamic patterns of interaction between team members, thus capturing how learning unfolds over time. To promote the integration of the dynamic nature and temporality in researching team learning, we here provide a definition of interaction dynamics, the central tenets that can be used for capturing team temporal phenomena. We define interaction dynamics as *"micro-behaviours forming patterns that continuously change, emerge and evolve throughout a team's lifecycle of interaction"*.

Studying interactions in a dynamic way enables researchers to capture 'what happens' rather than 'what is' (see Roe, 2008). Through investigating real team interaction, research questions can evolve from how team learning behaviours are *perceived*, to how team learning behaviours actually *are*. For example, one may look for mechanisms and characteristics associated with team learning and performance under different contexts or interventions, and how these are affected, facilitated or hindered by internal or external variables such as shifts in workload, team membership changes, stress or unexpected events.

One might argue that dynamics can also be researched through higher-level team behaviours that are captured, for example, through observational research, thus also offering a means of understanding what happens. However, such a methodology might not offer the possibility of studying the connections, relations, and patterns between the exhibited behaviours to the level of scrutiny that would enable the detection of emergent states or changes in these states over time. By considering interaction dynamics as micro-behaviours that continuously change, and through using the appropriate methodological approaches to capture micro-behaviour patterns, researchers enable a detailed, effective, and efficient investigation of emergent states and otherwise undetectable details of team learning. What is more, such states and details can be captured and traced in both small-scale and more complex, interconnected teams and systems. For example, one can study a single small-scale team during one learning event (e.g. interaction within one flight controller team in NASA's Mission Control), but can also study, on a micro-level of detail, the interaction of larger-scale systems (e.g. interaction between all flight controllers in NASA's Mission Control) or even entire organisations (e.g. interaction between NASA's Mission Control, Astronauts, other support staff across all NASA field centres in the U.S.), and how these interact and learn from each other during the same event. Understanding team learning in such a micro-level of granularity helps develop and establish both formal and informal learning opportunities and interventions that can be introduced in the right place, at the right time. It is therefore important to find methodologies and develop apparatus that enable the procurement and analysis of such interaction dynamics.

Exemplary, technological developments enabling the collection of fine-grained interaction dynamics are sociometric badges (Kim et al., 2008, 2012), body sensors (Dong et al., 2012), or video and audio recording of team communication and behaviours (Klonek et al., 2020). Attempts are being made to incorporate these technologies in research across the domains of organisational psychology (Klonek et al., 2019), business management (Lehmann-Willenbrock & Allen, 2018), and educational sciences (Lämsä et al., 2021). However, investigation of interaction dynamics remains scarce due to the lack of accessibility to data collection or analysis methods, and the factual or perceived complexity of utilising the respective data analysis techniques.

It is our ambition to guide our readers towards a more practical and seamless application of researching and analysing fine-grained interaction data for modelling and understanding professional team learning. This chapter provides a rationale for designing and carrying out interaction research, by following the same order as this of the key steps that should be adopted by researchers: (a) defining the interaction dynamics of interest with respect to team learning, (b) choosing an appropriate data collection method, and (c) choosing an analysis technique that captures temporality.

9.2 Team Learning and Interaction Dynamics

A first step in designing research involving interaction dynamics is defining which patterns are relevant to our phenomenon of interest: team learning. It is thus vital to first envisage what team learning entails.

Research on team learning picked up after Edmondson (1999) defined the phenomenon as a behavioural cyclical process of seeking, collecting, experimenting, reflecting, and discussing information. The term has since then received multiple definitions, a lot of them embracing the idea that team learning is a temporal phenomenon, to be studied at the team-level, involving different processes, and leading to different outcomes (Decuyper et al., 2010; Wiese & Burke, 2019). Understanding how and which interaction dynamics can be used in the investigation of team learning involves first identifying what are the possible team learning processes whose interaction can be useful to researchers. An exemplary model is the integrative model of team learning by Decuyper et al. (2010). It delivers a model on team learning recognizing the importance of emergent states and positioning these in relation to team learning processes. Hereby, this model is exemplary in modelling teamwork in general, and team learning specifically (Van den Bossche et al., 2022).

Historically, research in team learning has been strongly influenced by an input-process-output model, where team processes describe the mechanism by which individual team members resolve tasks (Dillenbourg, 1999; Kozlowski, 2015). However, it was made clear that it is necessary to differentiate between the various types of process variables (Marks et al., 2001). Important variables such as group potency or cohesion, do not denote interaction processes. Decuyper et al. (2010) proposed to call them 'emergent states', constructs that describe cognitive, motivational and affective states of the team, and these are different from the team interaction itself. As such, emergent states do not represent team interactions, they are products of them and become new inputs to subsequent processes. For example, teams with low psychological safety (as an emergent state) may be less willing to share knowledge (as a process), which in turn may impact psychological safety.

In relation to the team learning process, the team learning model by Decuyper et al. (2010) presents seven categories of team learning processes: (1) sharing, (2) co-construction and (3) constructive conflict; (4) team reflexivity, (5) team activity and (6) boundary crossing; and (7) storage and retrieval. These team learning processes take the team towards adaptive, generative or transformative learning. These outputs are sometimes immediately observable in changing team performance. However, often they remain conceptual, as changes in the teams' capability to act differently. With regard to the emergent states as proximal outcomes of the team processes, this model points to exemplary variables such as shared mental models, team psychological safety, group potency, team efficacy, and cohesion.

Up until this point, we have presented the processes or concepts related to team learning without really focusing on their dynamic nature. It is important to understand here that all aforementioned processes are tied to time, meaning that they emerge, evolve, and develop differently throughout a team's single performance episode or entire life cycle. Raes et al. (2015) found that effective team learning is bound to the ability of a team to engage in sharing through "a sequence of successive and constructive verbal behaviours that construct meaning" (p. 491). Therefore, to investigate team learning dynamically, it is important to consider the interactions of team members related to these processes as they unfold during teamwork, revealing with temporal detail the structural combinations of behaviours desirable for effective team learning. But how can we do that?

It is important to first understand what different interaction dynamics exist, before connecting them to team learning.

9.2.1 What Are Interaction Dynamics?

Earlier, we defined interaction dynamics as micro-behaviours forming patterns that continuously change, emerge, and evolve throughout a team's lifecycle of interaction. Given the broad range of micro-behaviours that exist, we categorise them as either (a) feature-based, or (b) essence-based. The various combinations and development of both types of micro-behaviours into different patterns throughout interaction comprise interaction dynamics.

(a) *Feature-based micro-behaviours* include behaviours or events defined entirely by their inherent features (form, shape, proportion), and their classification as such depends on their concrete characteristics, independent of any interpretations. For example, speech acts (who talks to whom, for how long, how loud, etc.), physical proximity, movement energy (Onnela et al., 2014), or even positioning in the room (Ciolek & Kendon, 1980) are concrete behaviours, largely defined by specific inherent features, and may reveal a development or change in interaction (De Ruiter & Loth, 2016). Feature-based micro-behaviours may also include manipulation of objects or interactions with interfaces, such as clicks on a display, or eye gaze at a screen.

(b) *Essence-based micro-behaviours* consist of any behaviour or event for which the content of information is indispensable for its definition, and some kind of meaning attribution is necessary to classify it as such. Essence-based behaviours are of more abstract nature and constitute higher-level behaviours than feature-based ones, valuing the quality of information over the lower-level, concrete features of the behaviour itself. For example, 'providing positive feedback', 'suggesting', or 'directing', are essence-based micro-behaviours, since capturing such behaviours involves not merely collecting speech acts, but rather providing meaning to the content of the information exchanged in these acts.

We argue here that it is not only about which micro-behaviours are present during team interaction, but also how these micro-behaviours interconnect forming different interaction dynamics, and how various patterns change depending on environmental influences. Even though the stability, growth, and recurrence of structural patterns underlying temporal phenomena develop and change over time (Roe, 2008), little is known about how these unfold and relate to the phenomenon of team learning. Dynamic patterns of interaction can give insights into *how* teams learn (e.g. pattern combinations, emergence of new patterns, etc), or *when* teams learn (e.g. moments where emergence of different patterns occurs), thus helping to inform the design of interventions for the promotion of team learning processes.

For example, spotting the development of learning triggers (Wiese & Burke, 2019) can help in facilitating learning or manoeuvring away from delays in the learning process. Learning triggers are presented in the work of Wiese and Burke (2019) as catalyst events for team learning, where exposure to an event causes a spark or a disruption of the learning process. For instance, communication patterns involving positive statements by the team leader followed by agreement from all team followers might cause an increase in a team's knowledge state, which may be temporarily hindered when patterns revealing differences in opinion from the followers emerge. In other words, studying patterns of behaviours temporally can help in answering research questions around what mechanisms pose "learning triggers" (e.g. agreement between leader-follower), as well as whether and how the emergence or disappearance of these learning triggers is associated with specific contextual or procedural events during team meetings (e.g. disagreement between leader-follower after a leader makes a mistake).

It is therefore important not only to associate micro-behaviours to team learning, but also investigate their dynamic nature in greater detail. Research relating micro-behaviours to phenomena or constructs that are closely tied to team learning, such as sharing or co-construction (Decuyper et al., 2010; Van den Bossche et al., 2011; Wiese & Burke, 2019), set a strong starting point for developing assumptions on dynamics that facilitate or impede learning. By doing that, researchers open the door towards the investigation of questions related to the exact moments at which team learning is promoted or impeded (*when*), as well as to the mechanisms by which this promotion or decline is manifested (*how*).

In the following sections, we examine how team learning can be conceptualized through feature and essence-based micro-behaviours, to inspire our readers to choose the appropriate micro-behaviours for their research. We also explore through examples the added value that interaction dynamics captured via these micro-behaviours may have on team learning research.

9.2.2 Connecting Team Learning Processes to Interaction Dynamics

Any research strategy that attempts to understand temporal phenomena such as team learning involves first identifying which phenomena should be studied, before exploring their temporal relationships and their long-term stability and change (Roe, 2008). Therefore, any sampling decisions on how and which data to gather should be directly related to which interaction dynamic is of interest to the research's aim.

As discussed above, both essence- and feature-based dynamics can provide information on team phenomena, and both can give insights into the question of 'what happens' during interaction. Depending on the chosen research question, researchers may opt to either focus on essence or feature micro-behaviours, or combine both and possibly study their interaction. For example, a researcher interested in understanding the process of how *sharing* unfolds during an event may investigate the essence-based patterns formed between different information sharing micro-behaviours (e.g. fact sharing, interpretation sharing, and projection sharing; see Uitdewilligen & Waller, 2018). In addition, that same researcher may choose to also assess how this process of sharing combines and evolves across team members, and so also investigate feature-based micro-behaviours of actor relationships (e.g. conversational turn-taking patterns across team members; see Gorman et al., 2019). Other feature-based interaction dynamics, such as information flow, flexibility, complexity, or high mimicry during learning (Kim et al., 2012), can also be used as proxies for understanding processes of team learning. Below, we provide certain pilar examples of research done in team interaction dynamics and connect these to the team learning emergent states and processes mentioned earlier.

An interesting example of research investigating the interaction dynamics of essence-based micro-behaviours was done by Kolbe et al. (2014) in healthcare, who researched sequences between essence-based behaviours revealing implicit coordination behaviours (e.g., providing assistance, giving information without request) or explicit ones (e.g. giving information upon request, instructing). They found that higher team performance is associated with significantly more patterns combining implicit coordination behaviours followed by explicit coordination behaviours. Even though their study was not directly associated to team learning, the behavioural patterns researched may also reveal interesting information with respect to our phenomenon of interest. More specifically, implicit behaviours are related to the existence of team mental models and trust (Burtscher et al., 2011; Rico et al., 2008), while explicit behaviours reveal opportunities for the development of shared understanding and co-construction (Salas et al., 2007). Therefore, understanding the dynamic interchange between the two types of behaviours reveals the undergoing structure through which teams inform, develop, and use their shared mental models throughout interaction.

Another example, this time using feature-based micro-behaviours to capture interaction dynamics comes from the research of Gorman et al. (2019), who investigated action teams by modelling the actors speaking at each second in a team meeting. The researchers calculated the recurrence of turn-taking patterns throughout teams' meetings, to determine the reorganisation of communication in response to environmental perturbations. Findings showed that novice teams were not as quick or as successful in reorganising their information as compared to experienced teams. This finding possibly reveals that reorganising information is not only an important skill for performance, but it is a skill revealing that preceding effective team learning has occurred.

Within the educational domain, interaction patterns were researched to identify phase transitions during collaboration. Ricca et al. (2019) coded feature-based turn-taking patterns of team members and how these reoccurred and changed throughout interaction. They also qualitatively marked the points of phase change within collaboration (e.g., problem scoping, generating ideas, reporting, testing) and found that the points where turn-taking patterns changed collided with the points of phase transitions they had noted, thus showing that turn-taking behaviour not only changes during interaction but is also a good indicator of how and when a team moves from one phase to another. Team learning research can use such indicators of phase transition to research the effectiveness of interventions or note the times at which a team requires an intervention.

Comparing interaction dynamic peaks using turn-taking behaviours is also a promising way of monitoring environmental changes (transitioning from task to task), and understanding team interaction structures that lead to increased effectiveness, cognitive stability, or flexibility (Stevens, 2012). Such interaction dynamics can also be used to identify boundary crossing, as patterns have been found to collapse when a team goes through a phase transition (Kugler & Turvey, 1987; Wiltshire et al., 2018).

Interaction dynamics may also be used to reveal the emergence of joint attention, which is useful for creating a common ground and engaging in active collaboration. For example, in aviation research, joint visual attention has been used to understand pilots' coordination strategy during teamwork. Gaze alignment was used to indicate engagement in joint activity or overlap in information acquisition, while misalignment indicated divergent activity and sharing of task-load (Gontar & Mulligan, 2016). The investigation of different eye-gaze patterns development during task-work can further reveal learning behaviours such as adaptive coordination through early acknowledgement of changing situational demands requiring joint or divergent activity.

We have provided some examples of how both feature- and essence-based micro-behaviours can be used to examine interaction dynamics and to understand processes and states related to team learning. We now move on to presenting some ways through which this data can be gathered and coded, before delving into the analysis techniques that enable the investigation of the dynamic nature of interactions.

9.3 Researching Interaction Dynamics: How Do I Gather Data?

Having first identified the interaction dynamic of interest to the research's aim, the second decision step of investigating interaction dynamics includes choosing a data gathering and coding method (Lehmann-Willenbrock & Allen, 2018) by assessing their appropriateness in capturing the corresponding temporal granularity of the phenomenon of interest.

Interaction dynamics may differ with respect to their temporal resolution, and some data collection and coding methods may lead to representation of the dataset that is of a higher or lower temporal resolution; that is, the detail at which the dataset is represented and the phenomenon at hand captured and broken down. High resolution refers to a more exhaustive representation of the dataset. For example, dynamics based on behavioural changes of milliseconds (e.g. change in eye movements, change in loudness level of speech) are of higher temporal resolution compared to dynamics based on higher-level constructs (e.g. communication types such as defending one's own position).

9.3.1 Data Gathering Considerations

There are multiple ways of gathering team interaction data. Direct observation is one means of gathering data, however, human observers may not be as fast or as reliable in recording the necessary behaviours as these are being observed, while semi- or fully-automated real-time data transcription or coding methods have only recently started getting validated (Bokhove & Downey, 2018). Other than direct observations, video and audio recording are so far two key means through which temporality in interaction can be captured, as they offer the choice to replay, check, and reuse of the data. Especially with the rise of small-scale devices, such as action cameras and 360-degree cameras, etc. this opens up a world of possibilities to record team meetings for longer periods of time, in an unobtrusive and low-cost manner. In addition, in the past decade, methods from computer science have been developed to unobtrusively capture and analyse interpersonal behaviour, also called social sensing (Schmid et al., 2015). As many smartphones and smartwatches already are equipped with camera, microphone, accelerometer and GPS, the challenge is not anymore on recording the data, but on developing the right data extraction methods (Schmid et al., 2015). Moreover, sensors fully dedicated towards recording (and analysing) feature-based micro-behaviours in social settings, such as the sociometric badges (Onnela et al., 2014), have been developed and are further discussed below.

9.3.2 Data Coding Considerations

Software developed for video and audio manipulation offer the ability to either transcribe and then code (e.g. Atlas.ti; AmberScript), or code directly on the video noting the temporal stamp of each behaviour (e.g. Observer-XT; Noldus et al., 2000). Coding schemes differ with respect to the number of behaviours they include, the extent to which these behaviours relate to the task at hand or to a specific phenomenon, and the level of abstraction (Waller & Kaplan, 2018). Coding of interaction data, especially when it comes to essence-based behaviours, may involve to some extent a reduction from the complexities of actual behaviours to broader categories, thus inhibiting an exhaustive representation of interaction, and following a top-down, theory-driven quantitative approach rather than a bottom-up exploration of interaction (Stivers, 2015).

It is important to consider the extent to which the research requires the identification and analysis of micro-behaviours with high or low temporal resolution. Depending on the research aims, the combination of essence-based coding schemes with feature-based data (e.g., speaker-receiver information) can also be used to account for any disregarded essence-based changes in interaction dynamics that might be overlooked. For example, a researcher can use essence-based micro-behaviours of problem solving processes (e.g. information provision, information request, option generation or solution evaluation) to spot phase transitions during team collaboration (Wiltshire et al., 2018). Transitions can also be spotted via coding and analysing actor turn-taking patterns across the meeting (Ricca et al., 2019).

Validated coding schemes that can help with the incorporation of interaction dynamics related to team learning are already available (see review of Brauner et al., 2018). For example, the Co-ACT coding scheme by Kolbe et al. (2013) can be used to research implicit and explicit coordination processes (Kolbe et al., 2014). The coding scheme of Raes et al. (2015) can be used to code different types of basic team learning behaviours with lower temporal resolution. The Act4Teams coding scheme of Kauffeld et al. (2018) includes four types of team interaction (problem-focused, procedural, socioemotional, and action-oriented) and especially the analysis of the problem-focused communication shows how teams share knowledge, generate new ideas, etc.

All aforementioned coding schemes can be applied to data records (video, audio, or text based) using software such as the Observer-XT (Noldus et al., 2000), Interact (Mangold, 2020), or CAT (Klonek et al., 2020). Other examples of coding schemes for micro-coding, as well as available software can be found in Waller and Kaplan (2018).

9.3.3 Towards a Combined Data Gathering and Coding Methodology

The coding process of datasets of high-temporal resolution can be very labour-intensive. So far, most research on team interaction dynamics involves manual coding of the data before analysis. However, more recently, technological innovations such as behaviour sensor systems, or machine learning algorithms (e.g. Bonito & Keyton, 2018) are attempting to ease the coding process by automating the acquisition of meaningful information. Here we exemplary introduce two options for (semi-)automated process of coding behaviours.

9.3.3.1 Behaviour Sensor Systems

Sociometric badges are a sensor technology device enabling the automatic collection and measurement of interactions (Kim et al., 2012; Olguín Olguín et al., 2009). The installed sensors in the device enable the collection of data identifying face-to-face interactions (infrared sensor), speech features (microphone audio-signal), and mimicry patterns (accelerometer). Sociometric badges offer a bundle of services since collection and coding are both done automatically via the badges. However, lately the downsides of these commercial all-in-one devices have come to light: as the underlying algorithms are company-secret information, researchers have tried to validate these sensors with disappointing results (Kayhan et al., 2018) next to the problem of malfunctioning badges and synchronization problems (Endedijk et al., 2018).

9.3.3.2 Supervised and Unsupervised Machine Learning

With digitalization pushing forward, automated coding solutions have also become available, such as automatic coding filters to code different communicative functions (Erkens & Janssen, 2008). More recently, advancements in automated content analysis have also started to incorporate supervised machine learning (SML) as a technique to automatically code transcribed datasets. SML is the process of training an algorithm to identify relationships between input (text) and output variables (codes) from a specific dataset, so well that the machine is then able to identify any relationships between text and codes in new datasets. For example, assume that you code one transcript, thus associating text content to a specific code, (e.g. a sentence including “I suggest we incubate her” is coded under the label “suggestion”). This association between content–code is used to train your algorithm to automatically spot content that falls under this code in other, unknown transcripts. For an illustration of how SML can be used in practice, see Bonito and Keyton (2018). Note that SML is a deductive, top-down process as it requires training algorithms based on existing codebooks.

Although more challenging, unsupervised machine learning can be used as an inductive, bottom-up process of identifying text clusters and structures within a dataset, enabling a researcher to choose the most interpretable set (Lambert, 2001) and thus offering the chance for exploratory research with no pre-existing codebook. Unsupervised machine learning can also be applied to datasets including feature-based micro-behaviours such as posture or eye gaze (Huang et al., 2019).

9.4 Researching Interaction Dynamics: How Do I Analyse My Data?

9.4.1 Developing a Framework for Choosing a Data Analysis Technique

Having defined interaction dynamics as patterns that continuously change, researchers are called to use analysis techniques that can help them capture this continuous, or near-continuous nature of the data they gather. Different techniques can be used, depending on the research's aim and purposeful insights. There is an increasing call for the incorporation of such techniques in research (David et al., 2021; Herndon & Lewis, 2015; Leenders et al., 2016). To ease their incorporation, we present our readers with the DATS framework (referring to Data Analysis Technique Selection); a framework for choosing an analysis technique based on two key aspects: the *units of analysis*, and the *dynamic output generated*. The framework is described below and illustrated in Fig. 9.1.

The *unit of analysis,* referring to the key units or data points that are modelled in the analysis, can be:

(a) *Actor-oriented*, where actors (team members) in the dataset are incorporated in the analysis
(b) *Behaviour-oriented*, where the behaviours (essence-based or feature-based) are incorporated in the analysis

The two are not mutually exclusive, meaning that one analysis technique can combine both actor-oriented and behaviour-oriented units of analysis.

The dynamic output generated can be on:

(a) *Qualitative dynamic patterns*, referring to understanding the composition of each pattern. The term 'qualitative' here refers to the fact that the content and interpretation of each behaviour that makes up the pattern are of central focus, and the term dynamic refers to considering the order in which behaviours occur. It can be based on essence-based behaviours, for example examining whether an action-oriented behaviour is being followed by an information-oriented behaviour (Kolbe et al., 2014), or in relation to feature-based behaviours, for example exploring the development of inertia or recency patterns in actor sequences (Butts, 2008; Leenders et al., 2016).

	Structural qualitative dynamics	**Structural quantitative dynamics**
Actor-oriented	Analysis techniques that focus on actors and can provide qualitative information between actor patterns	Analysis techniques that focus on actors and can provide quantitative information on actor patterns
Behaviour-oriented	Analysis techniques that focus on behaviours and can provide qualitative information on behaviour patterns	Analysis techniques that focus on behaviours and can provide quantitative information on actor patterns

Fig. 9.1 DATS Framework for temporal analysis technique selection

(b) *Quantitative dynamic patterns*, referring to number of occurrences of each pattern, number of components, frequencies, distributions. Information on the timing of each quantitative output is necessary for a method to fall under that category (hence labelled 'dynamic').

Again, the two are not mutually exclusive and can both be generated from the same analysis technique.

In the following section, we list the main temporal techniques that enable the investigation of interaction dynamics and their temporal underpinnings. We use the DATS framework to categorise each technique based on the units analysed and the output generated (see Fig. 9.2). To highlight the use and added value of each technique, we provide some examples of research that can be done using each technique in the context of team learning.

9.4.2 Pool of Temporal Analysis Techniques

We apply the DATS framework on a representative, yet not exhaustive pool of five temporal analysis techniques, namely sequential analysis, relational event modelling, process mining, non-linear time series analysis, and T-pattern analysis. In Fig. 9.2, the techniques are classified based on their actor or behaviour-oriented units of analysis, as well as their qualitative or quantitative dynamic output. We also provide an overview of each technique, however getting into details on how each can be applied is beyond the scope of this chapter. For more information on the requirements of the presented techniques see David et al. (2021).

Actor-oriented	Relational Event Modelling T-pattern analysis	Non-linear, time-series analysis T-Pattern analysis
Behaviour-oriented	Sequential Analysis (LSA, FSM) Process Mining T-Pattern analysis	Non-linear, time-series analysis T-Pattern analysis
	Structural qualitative dynamics	**Structural quantitative dynamics**

Fig. 9.2 DATS Framework applied on pool of temporal analysis techniques

Sequential Analysis Analysis techniques that fall under this category are lag sequential analysis (LSA; Bakeman & Quera, 2011; Quera, 2018) and frequent sequence mining (FSM; (Zaki, 2001). LSA considers the order of behaviours in the data and identifies statistically significant direct or indirect transitions from one behaviour to another (A→B or A→C respectively), thus identifying pattern sequences. The main use of LSA is to identify sequential patterns of behaviours, thus providing structural *qualitative* information on *behavioural-oriented* patterns. It also calculates frequencies, probability and significance of transitions as well as information on the strength of association.

Different from LSA, FSM detects sequences of behaviours that occur more often than a minimum level in a dataset (e.g., 10%). Combinations of different sequences of behaviours are introduced by the coder and the analysis identifies sequences and sub-sequences that occur above a customized threshold in all defined sequences. FSM thus focuses on *behavioural* units and generates frequencies of varying sequences (Chen et al., 2017). Even though the order of the behaviours is considered, LSA and FSM do not provide information on the exact moment in time at which certain sequences are present, or how they evolve differently throughout an interactive meeting, thus neglecting structural quantitative aspects as we defined them. A research paper that can be used as tutorial for applying this technique in the context of team learning is by Kolbe et al. (2012).

Sequential analysis can be used to answer questions relating to the likelihood of event sequences to exist at different phases during a meeting, at different points throughout a team's life-cycle (comparison of different meetings), or at different teams in an organization exposed to similar experiences. A simplified example of how sequential analysis can be used in the context of team learning is to assess the process of *co-construction* during a learning event. During training, co-construction involves engaging in "repeated cycles of acknowledging, repeating, paraphrasing, enunciating, questioning, concretizing, and completing the shared knowledge, competencies, opinions or creative thoughts" (Decuyper et al., 2010). Researchers can use these behaviours to code a communication dataset, and explore the nature of co-construction with LSA by seeing how these behaviours form different sequences, and which sequences are more likely to occur at different moments in time.

Relational Event Modelling (REM) REM shares ideas with network systems theory (Herndon & Lewis, 2015; Klonek et al., 2019; Lehmann-Willenbrock & Allen, 2018), which views teams as a system consisting of nodes (actors) and links (relationships between actors). REM assumes that past relationships between actors shape future relationships and interactions; that is, every sequence of events between actors depends on the immediately preceding events (Butts, 2008; Butts & Marcum, 2017). Relational events consist of a sender, a receiver and a timestamp, and reveal interaction dynamics such as inertia, referring to the degree to which a member's past contact will be their future contact, or recency, referring to the degree to which a member's most recent contact will be their future contact (for more patterns see Marcum & Butts, 2015). REM gives actor-oriented information of *qualitative* nature (different ways in which relationships occur). The frequency and significance of sequences are also provided, but there is no output related to their exact temporal stamp. A paper that can be used as guide for applying REM in team research is by David and Schraagen (2018).

REM could be used to assess how actor relationships are affected by immediately preceding events and how these change for example after the incorporation of a new team member. Different patterns of actor relationships can be examined and modelled on the dataset, such as the aforementioned inertia (e.g. negative inertia would indicate searching behaviours on whom to share information with).

Even though we only focus on REM in this chapter, note that other techniques and stochastic actor oriented models (SAOM; Snijders, 2001) of the social network analysis family could also be used in interaction dynamics research (for review and examples see Borgatti & Foster, 2003; Lusher et al., 2010; Robins, 2015).

Process Mining Process mining includes data mining methods such as Petri Nets or Finite State Machines (Robero et al., 2010). It includes modelling the data in process models that consist of nodes (event classes) and edges (connections between nodes). The two key parameters examined within these models are the significance (how important nodes and edges are) and correlations (how closely related events following one another are) between data points. Process mining can be inductive, including model discovery (e.g. Heuristic Miner; Weijters et al., 2006) and thus enabling the investigation of the temporal structure of events and discovery of unknown sequences between them. The technique also offers conformance checking, where one can assess the extent to which a process model generated from one dataset differs from another dataset (Van der Aalst, 2012). Process mining is mostly behaviour-oriented as it assesses the structural composition between micro-behaviours without considering the involved actors. Its output reveals qualitative dynamics by offering the ability to assess the content of the patterns discovered. Software support for process mining is included in the ProM framework (Van Dongen et al., 2005) providing guidance and tool support for process analysis.

An example from research that can be used as a tutorial for applying process mining to team learning context is the research by Engelmann and Bannert (2021), who investigated cognitive and metacognitive events in self-regulated learning, and found that unfolding interaction sequences between team members, unlike popular belief, included weak connections to metacognitive behaviours.

Non-linear Time-Series Analysis This category includes a variety of methods such as Recurrence analysis, Phase or state space analysis, Hurst exponent, Lyapunov exponent and entropy (Guastello, 2017). They all deal primarily with interval data, although variations of each analysis also enable their application in discrete interaction sequences of ordinal spacing (e.g. Gorman et al., 2012, 2019). This type of analysis assesses whether data points in a time-series are recurrent or random. Depending on the data modelled, the unit of analysis can be both actor or behaviour-oriented, with output revealing structural quantitative dynamics.

While non-linear time-series analysis is performed through different techniques, a paper that discusses and guides its readers through the application of state space grids is that by Meinecke et al. (2019). In their paper, Meinecke and colleagues showcase step-by-step how to investigate the development of team problem-solving behaviours by comparing patterns of interaction between the first and final team meeting. Non-linear time-series analysis can also be used to model existing or known team learning processes, or spot new, emergent states within a team learning event.

T-Pattern Analysis TPA is a mixed method, aimed at detecting patterns in a dataset that would be undetectable by a naked eye (Magnusson, 2000, 2018). Any T-pattern is made up of a criterion and a target behaviour that constitute a T-pattern if these fall adjacent to one another within a time-dependent 'critical interval'. Small T-patterns (*ab*) may also be part of larger patterns (*abcd*). TPA detects hierarchical pattern compositions and visualises how these unfold in different ways over time, thus providing both structural *qualitative and quantitative* information on *behavioural* patterns. It can also provide both types of structural information for actor-oriented units, as it is also able to yield information regarding the involvement of actors and actor switches. However, it is not dynamically sensitive in terms of actors, as no information is available on the ordering of actors switches or how they unfold differently over time. TPA also generates further structural quantitative output regarding Monte Carlo validation, number of pattern occurrences, and number of components. It is the only method that applies to all four aspects of our framework, enabling the analysis of both behavioural and actor-oriented units, while yielding qualitative and quantitative structural outputs for both. For T-pattern analysis breakdown and step-by-step application see Magnusson (2017, 2018).

T-pattern analysis offers very good opportunities for the exploration and modelling of emergent states. Different or more complex patterns that would otherwise be undetectable could be traced to specific moments in time, thus suggesting possible emergence of a shared mental model, or a recognition of another catalyst emergent state.

Note that any of the methods can provide structural quantitative dynamics if a performance episode is segmented into different phases, thus enabling the comparison of pattern development across the different phases. Phases can be determined either based on certain events that occur within the episode (e.g. unexpected surprise), or based on standard time intervals. For example, SNA can provide dynamic output in interaction by comparing different networks across multiple phases within a performance episode. Also, depending on the needs of the research, different analysis techniques can be used isolated or in combination. For example, a non-linear time-series analysis can be used in combination with sequential analysis, to capture both structural qualitative and quantitative aspects of the data.

9.5 A Temporal Approach to Team Learning: Closing Remarks

Teams make up the nucleus of every organisation, collaborating and coordinating their activities to meet organisational goals. In the ever-changing environments in which teams interact, either due to changes in team membership, task demands, or other organisational structures, teams are called to learn and adapt. Organisations are thus called to embrace a culture of lifelong professional learning, integrating, and promoting formal, non-formal and informal learning experiences in their employees (Carr et al., 2018). Research has already shown that the processes making up team learning are continuous in nature. It is thus important for learning research to move past the static representation of team learning and start capturing its dynamic nature, which stems from the continuous team member interaction.

Throughout our chapter, we aimed to show our readers how interaction dynamics that reveal temporal changes in teamwork are a proxy for investigating and understanding team learning, its underlying processes, such as co-construction and constructive conflict, and its emergent states, such as shared mental models or psychological safety (Decuyper et al., 2010). Through examples, we tried to illustrate the added value and opportunities in researching on a detailed level 'what happens' both in small-scale and large-scale, complex, interconnected systems. As a closing remark to this chapter, we would like to highlight the three key takeaways for ensuring that team learning is studied as a temporal phenomenon:

9.5.1 Key Takeaways

(i) *Define the phenomenon of interest and determine any relevant interaction dynamics*

Processes and emergent states related to team learning can be studied through the investigation of interaction dynamics, which we define in this chapter as sequential patterns created between micro-behaviours that change throughout interaction. We break micro-behaviours down to two different categories, essence- and feature-based, thus easing the process of identifying relevant micro-behaviours that ought to be investigated in order to capture the temporality of the chosen phenomenon, process, or emergent state.

(ii) *Choose a data collection and coding method that can capture the chosen interaction dynamics*

We outline certain possibilities for data gathering and coding of micro-behaviours that can help detect interaction dynamics in the data. Data collection techniques like the ones mentioned in this chapter enable the investigation of team learning in the field rather than in controlled contexts, thus capturing interaction in actual organisational contexts. We see that there is an evolution from the time and labour-intensive coding, moving towards automatic ways of attaining data. But challenges still exist. State-of-the-art technologies such as sociometric badges are yet to be validated, while developers are not opening up in an understandable way regarding the transformation that occurs in automatically coded or analysed data. We call for the incorporation of more transparent technological methodologies, so as to ensure the adoption and incorporation of such techniques in team learning research.

(iii) *Choose an analysis technique that can help you capture temporality*

Lehmann-Willenbrock and Allen (2018), pointed out how researchers should start embracing existing methodologies and analysis techniques that capture temporality in the investigation of team learning. We stand by this claim and offer a framework for choosing such techniques based on their unit of analysis and the output they generate, alongside a pool of existing techniques. We also provide some examples and a study 'tutorial' that can be used for the application of these techniques and the incorporation of interaction dynamics in team learning research. Some of the studies that we refer to already deal with aspects that can also be investigated within the context of team learning, such as self-regulated learning by Engelmann and Bannert (2021), while others provide a detailed description of the analysis technique they used that can be applied by researchers in the field of team learning in the future.

We hope that our framework for data analysis technique selection will assist and foster the investigation of team learning, its processes, and its emergent states as these unfold over time, in actual organisational contexts where teams are faced with, and learn through true organisational challenges.

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