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REVIEW

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Toward the incorporation of temporal interaction analysis techniques in modeling and understanding sociotechnical systems

Lida Z. David[1] | Jan Maarten Schraagen[1,2] | Maaike Endedijk[1]

[1]Department of Learning, Data-analytics, and Technology, University of Twente, Enschede, The Netherlands

[2]Netherlands Organisation for Applied Scientific Research TNO, Soesterberg, The Netherlands

Correspondence
Lida David, Department of Learning, Data analytics and Technology, University of Twente, Enschede, The Netherlands.
Email: l.david@utwente.nl

Abstract

The increased complexity of modern sociotechnical systems (STS) necessitates the need for a manageable representation of their attributes, to augment our understanding and enable the development of ways through which we can increase their effectiveness, efficiency, and safety. Although many of the methodologies developed in the Human Factors domain map and investigate system properties and network structures, the inclusion of the temporal dimension in the analysis of STS remains limited. In this paper we present how modeling and visualization of STS can be augmented with the incorporation of temporal interaction analysis techniques that enable a micro-level, fine-grained analysis of data. We provide an overview of temporal analysis techniques by breaking down their main function, requirements, types of research questions they can address, and the visualization properties they offer, attempting to enhance their use in system analysis. This overview can assist researchers in selecting an analysis technique, enabling the incorporation of temporality in STS analysis, and helping towards the design of improved and safer systems and interventions.

KEYWORDS
dynamical systems, interaction patterns, micro-level analysis, Sociotechnical systems, temporal analysis

1 | INTRODUCTION

Sociotechnical systems (STS), referring to systems comprised of human and technological agents, figure prominently in risk assessment, system design, and safety research. STS vary in complexity, as they incorporate a large set of parameters including human agents, technologies, their tasks and goals, as well as their direct work space, broader work environment and organizational influences (Olsen, 2007). The increased complexity of modern STS necessitates the need for a manageable representation of their attributes, to augment our understanding and enable the development of ways through which we can increase their effectiveness, efficiency, and safety.

Early developed methodologies of STS analysis, such as Technique for Human Error Rate Prediction (THERP; Swain & Guttmann, 1983) or Technique for the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr; Shorrock & Kirwan, 2002) follow a reductionistic analysis approach. That is, they attempt to understand a system by investigating and aggregating information on the system's individual parts (Stanton, 2013; Waterson et al., 2015). However, such approaches do not consider the principle of bottom-up *emergence* that governs complex systems, which occurs as a system's components interact with each other, self-organizing in response to various individual- and team-level inputs, as well as environmental changes. This self-organization leads to the development of new or reformulated properties and processes, which are not directly visible from the mere aggregation of the system's parts or through the linear association between parts' inputs and system's outputs (Gorman, 2014; Gorman et al., 2019). Rather, they can only be understood through the direct study of the simultaneous inter-system interactions and environmental changes as they unfold.

Although many of the methods developed in Human Factors aim to map and understand the roots of failure in these systems (see Stanton et al., 2013), they tend to assume homogeneity over time and across agents and their interactions (Leenders et al., 2016). However, systems continuously reorganize and restructure (Arrow et al., 2004; Woods et al., 2010), and changes in subsystems mutually influence each other. Due to this continuous change, the predictive power of static human factors methods is limited, indicating a shortage in methodologies that can predict system behavior (Salmon et al., 2020). If we want to broaden the scope of STS research from focusing on the mere roots or outcomes of failure to what characterizes a system as being able to avert danger or recover quickly after turmoil, we need the incorporation of analysis techniques that can consider its moment-by-moment operation.

Several micro-level processes, referring to immediate human-human and human-machine interaction processes that continuously change as systems function, have been found to influence the emergence and stability of system structures. For example, the complexity of behavioral interaction patterns continuously changes to better fit situational demands (Gorman et al., 2019; Lei et al., 2016), whereas communication patterns develop into flatter and more decentralized structures as task complexity increases (Barth et al., 2015). Tracking micro-level processes as they unfold can help us discover otherwise undetectable patterns of interaction, social norms, or relationships that emerge and develop as systems function and self-organize. Through researching and modeling interaction processes, temporal models of analysis can offer insights into the design of stronger and more adaptable systems that can prevent or maneuver away from failure, and help in further informing the design of sub-systems or even multilayer STS. For instance, the efficiency of a system is reflected in the time taken for it to reorganize its structure in response to task demands (Gorman et al., 2019). By modeling the moments and duration of structure reorganization, one can locate the best opportunities for intervention, and inform better system training. Such insights may also reflect on the redesign of higher levels that encompass a lower-level system, such as hospital policies changing to meet the demands of healthcare teams.

It is therefore important for researchers to be able to incorporate micro-level temporal analyses in their studies, as well as to understand the added possibilities offered by using them in STS research. The goals of this article are to (a) outline the added possibilities offered by incorporating temporal interaction analysis techniques in STS research, and (b) aid the understanding and differentiation between temporal techniques based on their function, requirements, and application possibilities they offer.

To address these goals, the following section discusses the different levels of STS analysis offered by current systems ergonomics methods, aiming to convince the reader on the importance of using micro-level temporal analysis models in aiding and expanding STS research. The section after that presents an overview of temporal methods and how one can choose between them, to be used as a toolbox by researchers interested in pursuing the endeavor of incorporating them in their analysis. We end by a summary and conclusions, as well as some directions for future research.

2 | CURRENT CHALLENGES WITH STS METHODS

The premise of STS analysis is that social and technical systems interact and are built within an organizational design promoting optimal cooperation, productivity, satisfaction, and safety (Clegg, 2000; Eason, 2014). Within the domain of Human Factors alone, over 200 methods have been developed to foster the investigation of complex STS (Stanton et al., 2013), and that of similarly complex processes associated with such systems, such as Distributed Cognition (Stanton, 2013), Shared Mental Models (Cannon-Bowers et al., 1993), Interactive Team Cognition (Cooke et al., 2013), or Resilience (Hollnagel & Sundström, 2006). Each method takes a distinct approach to STS analysis and error conceptualization, with a diverse level of focus that targets the analysis of different aspects and system elements. Depending on the unit of analysis, some methods take a “micro-level” approach, thus researching individual attributes and immediate human-human and human-machine interaction, whereas others focus on a “meso-level” of analysis, emphasizing the whole system comprising individuals, teams, and organizations. Models may also take a “macro-level” approach, incorporating the investigation of multilayered systems (Grote et al., 2014; Hendrick & Kleiner, 2002). A short introduction to the central focus and challenges of each level is warranted, starting off at the highest level of analysis and ending at the lowest, micro-level of analysis, which comprises the level of focus of our temporal interaction analysis techniques. We end this section with a discussion of how these temporal techniques differ from other micro-level ones, and their added value over and above static approaches.

2.1 | Macro-level methods

Macro-level methods comprise the highest level of system analysis, and take a complex multilayered system approach. Methods at the macro-level view the system as part of a larger network of organizations, industries, and other regulatory bodies, whose interrelations comprise a multilayered system, representing and guiding operation of each system layer. The principal unit of analysis is the organization. Macro-level approaches are frequently used in accident analysis, spotting "soft spots" across the multilevels that comprise multilayered systems, and informing redesign processes. For example, System Theoretic Accident Model and Processes System-Theoretic (STAMP; Leveson, 2004) models how safety constraints are applied and distributed across the system's hierarchical levels, which span from team to organizational and governmental structures. It treats accidents as the result of poor interaction between the components of the system and the lack of successfully applying safety constraints developed to prevent from failure. Macro-level approaches have offered valuable insights on potential failures and hazards in multilayered systems compared to more traditional approaches (Underwood & Waterson, 2014). Still, they take a more homogenous approach to accident causation, aggregating the information available on system functioning without considering the temporal fluctuations in processes within each multisystem component.

2.2 | Meso-level methods

Meso-level methods take a more granular approach to system analysis, considering the immediate environment within which humans and machines interact, as well as the broader system and organization that comprise them. The primary unit of analysis in this level are teams and networks within an organization, thus taking a narrower, more scrutinizing view to system analysis than macro-level processes. Meso-level practices have also been defined as focusing on the interaction between micro-level processes (immediate human–human or human–machine interaction) and macro-level phenomena (interaction across systems). It should be noted, however, that the differences between a meso- and macro-level analysis are not always as clear, and experts have judged several methodologies as being representative of both analysis levels depending on the focus of each investigation (for details, see, Foster et al., 2020). Examples of methods that are used for meso-level analysis are Event Analysis of Systemic Teamwork (EAST; Stanton, 2013; Stanton et al., 2008), and Functional Resonance Analysis Method (FRAM; Hollnagel & Goteman, 2004; Hollnagel, 2012). EAST is a descriptive method that maps three layers of STS. The social layer, including relations between agents (human, technical, organizational), the task layer, representing the relations between the tasks that are performed within an STS, and the information layer, including the topics that are covered and exchanged between agents when they perform tasks. EAST captures and interconnects these layers in a holistic STS visualization, and has been used to model various complex system processes such as Distributed Cognition within a system (Stanton, 2013). On the other hand, FRAM is a representation of functional, rather than structural, interactions within the system. After describing the essential system functions, it considers their variability, and defines and monitors their resonance based on the functions' interdependencies. These and other meso-level methods approach a more granular process of system analysis compared to macro-level methods, through an analysis across different phases or tasks. However, the association between different system layers depends on aggregation of system processes, without considering how these processes unfold through time or how one process may influence another.

2.3 | Micro-level methods

Micro-level methods comprise the lowest level of analysis, and focus on the interaction between humans and their immediate surrounding environment. Analyses at this level focus on human to human interaction, such as verbal communication between team members, or human to machine interaction, such as behaviors or movements of humans during interaction with an interface or a chatbot. The principal unit of analysis is the individual. Commonly used micro-level analysis methods are related to Cognitive Task Analysis, such as the Critical Decision Method (Klein et al., 1989) and Applied Cognitive Task Analysis (Militello et al., 1997), or Team Assessment Methods such as Team Task Analysis (Arthur et al., 2005; Bowers et al., 1994). Micro-level methods also entail communication analysis, and are considered suitable for task and system representation.

Several micro-level processes, as short or abrupt as interruptions or silences, have been found to influence the emergence or stability of system structures (Koudenburg et al., 2017). However, many communication analysis techniques and methods at a micro-level have been disregarded by scholars for their inability to capture the context of operation within which they occur (Waterson et al., 2015). It is important to mention here, that even though this statement holds true when referring to mere frequentist analyses and aggregation of interaction processes, temporal communication analysis models (described in detail in the next section) are closely tied to context.

The events analysed with temporal models are indisputably tied to their temporal occurrence, enabling the consideration of the context within which they occur (including the spatiotemporal environment of occurrence, as well as the sequences of events that have preceded or follow any given event in a time series). In other words, the temporal timestamp of each event and interaction analysed enables the identification and association to contextual phases at which a particular interaction occurs. Temporal micro-level analyses can help assess human-human or human-machine interactions and inform system design, for example by capturing the complexity in the interaction processes of feedback loops in control systems made of multiple human-machine systems. Capturing complexity is important in creating efficient control systems, considering that a controller should not be more complex than the system it needs to control (Law of Requisite Variety; Ashby, 1956). Also, in their work, Lavelle et al. (2020) argue that only through the temporal sequential analysis of interaction patterns one can understand that adaptability has taken place, as it is a great means of detecting change in teamwork (defined as how team members collaborate or coordinate their actions) that can be mapped onto contextual change (e.g., change in task or system composition).

The majority of methods at a macro-, meso-, or micro-level that are not tied to time share four features that deprive them of the ability to fully grasp the dynamic nature of STS systems. These revolve around the aggregation and linearisation, as well as separation and description of measurements when studying STS (Knight et al., 2016). Aggregation and linearisation of otherwise dynamic constructs across time, assumes that the system under the time of investigation does not change, or does not change in a sufficiently meaningful way, and that all processes develop in an equally dynamic and predictable way. However, assuming homogeneity over time and across system components impedes the investigation of change that occurs as emergent states develop (Leenders et al., 2016).

Separating the constructs we aim to investigate, or trying to describe, in a qualitative manner, what unfolds over time, leads to information loss regarding the processes that actually take place as systems function. We do not mean to say here that such approaches are not important. On the contrary, qualitative methods have offered great insights on team development and have directed the construction of leading influential theories and concepts such as Leadership, Situation Awareness, and Decision Making. For example, by using Team Task Analysis to study leader identification and its effects on performance during emergencies in the OR, researchers have obtained insights on the importance of leadership during emergencies (Price et al., 2012). However, it provides the illusion of studying the dynamic process of team leadership formation without actually considering how the context and processes through which leader identification unfolds may hinder or improve OR performance. We therefore argue that even though relatively abstract concepts such as leadership or decision making provide a conceptual framework to guide research, actual insights on the structure underlying these processes offer a more precise diagnosis of system functioning, failure, and opportunities for improvement.

Micro-level temporal techniques can assist in this endeavor. For example, insights from temporal analysis techniques, either on "how" teams communicate or "when" change in communication occurs, can be used to inform interventions such as the design of guided debriefing processes or the development of ad hoc reflection processes (e.g., Schmutz & Eppich, 2017). Other insights, like the development and maintenance of closed-loop communication structures during emergencies (e.g., Van den Oever & Schraagen, 2021) can be used to inform simulation based team trainings to promote close-loop communication (e.g., Fransen et al., 2017). Design of interventions that are well-informed with regard to system changes and to the timing of these changes is crucial to the development of more effective, efficient and safe STS.

To our knowledge, the use of insights that stem from these techniques for intervention and system design remains scarce so far. In the section below we outline the micro-level techniques that can be used to explore temporal processes and provide insights that can ultimately inform system design and functioning. These techniques thus offer an opportunity to Human Factors' researchers to enhance their range and breadth of system investigation.

3 | USING MICRO-LEVEL TEMPORAL ANALYSIS TECHNIQUES TO INVESTIGATE SYSTEMS

To promote the incorporation of temporal interaction models into existing ergonomics STS methodologies, we begin by (a) describing the main theoretical underpinnings that these techniques share, and (b) providing an overview of the techniques with their main function, requirements, and associated types of research questions they can address.

3.1 | Theoretical underpinnings of micro-level temporal analysis

The theoretical basis of temporal analysis techniques stem from complexity science, which revolves around developing new ways for studying regularities, and reducing the complexity of the world around us to manageable and predictable components (Phelan, 2001). It follows the premise that complexity arises from a simple set of "generative rules" that determine how agents within a system behave and interact over time. Each theory stemming from complexity science summons fundamental dogmata underlying system functioning that can assist in the development of analysis techniques capable of capturing system properties. Temporal models are mostly based on complex adaptive systems theory and nonlinear dynamical systems theory, while they are also closely tied to network systems theory.

The central tenets of these theories are that systems are characterized by components that exhibit nonlinear, sometimes chaotic relationships (Ramos-Villagrasa et al., 2018). That is, any action of one component can generate different results based on the state of all components at any given point in time, the input they receive, and the context of the interaction. Systems show a certain degree of variability, constantly moving across different states. This movement and constant change forms dynamic trajectories from state to state that are characterized by *self-organization* and *emergence*, making them difficult to predict (Meinecke et al., 2019). Nonlinear dynamical systems further posits that systems include *fractals*, that is patterns at higher system levels that show self-similarity in their structure with patterns at lower levels, and have a top-down effect on shaping and constraining lower-order interactions (Mandelbrot, 1983). Additionally, the concepts of law of requisite variety (Ashby, 1956) and local-global congruence (Gorman et al., 2017) are important theoretical underpinnings of system theories. The former, also mentioned earlier, pinpoints how complexity of interactions within a system should not exceed the complexity of the system itself, and the latter highlights how local variability (i.e., variability in micro-interactions) is a reflection of global stability (i.e., system functioning on a larger timescale).

The concept of temporality is directly tied to all aforementioned tenets, defining systems as adaptive networks of interchanging components with complex and dynamic relationships. To understand the dynamic interaction of systems, researchers should be able to thoroughly study and incorporate temporality in their studies. Bartunek and Woodman (2015) distinguish among five dimensions of temporality characterizing how processes and activities may develop and unfold. These dimensions are Sequence, Rhythm, Pacing, Polyphony, and Timing, and can help differentiate across different research foci and develop research questions tied to the concept of time.

3.1.1 | Sequence

Sequence refers to the temporal ordering of events and how these unravel within different stages of a performance episode. The duration of these stages, and the location of events within a sequence are important to consider.

3.1.2 | Rhythm

Rhythm concerns repetitions of cycles, including periods of stability and periods of change. Rhythm may be defined by long periods of disorder followed by short periods of stability ("focused" rhythm), or short periods of disorder followed by long periods of stability ("punctuated" rhythm). It may also be equally distributed between stability and disorder ("regular" rhythm) or be continuously altering between the two ("temporally switching").

3.1.3 | Pacing

Pacing refers to the speed at which activities occur. Speed may be studied on the overall performance episode under investigation, or during important stages within a performance episode. Speed is considered especially important during a stage at which reorganization is necessary due to environmental influences, as initiating change fast helps avert inertia.

3.1.4 | Polyphony

Polyphony refers to structural aligning and overlap of activities, or influence of one activity on concealing, replacing, or amplifying another.

3.1.5 | Timing

Timing may refer to: (a) possibilities for action that may appear simultaneously; (b) the alternative between acting or processing information that becomes available; (c) "timing norms" formally or informally set by organizations, forming periodic change of events either due to abrupt environmental changes, or regardless of the surrounding environment (set clockwork changes); (d) "windows of opportunity" that represent the most appropriate time to act or infer change.

The temporal micro-level interaction techniques listed in the following section provide a means of studying these temporality dimensions. Temporality dimensions can and have been used to differentiate between research perspectives and research questions related to dynamic systems (Bartunek & Woodman, 2015; McComb & Kennedy, 2020). We therefore use them to differentiate between the application possibilities of these analysis techniques.

3.2 | Overview of temporal interaction analysis techniques

The techniques that we discuss are extracted from recent reviews of temporal team modeling, reviewing techniques with theoretical underpinnings on complexity and network systems theory (Herndon & Lewis, 2015; Klonek et al., 2019; Lehmann-Willenbrock & Allen, 2018), complex adaptive systems (McComb & Kennedy, 2020), and nonlinear dynamical systems (Ramos-Villagrasa et al., 2018). Inclusion criteria entailed: (1) techniques focusing on micro-level analysis of immediate individual-to-individual (or individual-to-machine) interaction, which (2) consider the (spatio-)temporal stamp of each interaction, and which (3) search for complex patterns in interaction. Excluded were techniques that cannot capture high complexity in interaction patterns, but rather follow a more high-level approach to interaction analysis (e.g., growth curve modeling; Collins et al., 2016). The final list of techniques discussed consists of: Lag-based sequential analysis, T-pattern analysis, Relational event modeling, Recurrence analysis, Phase space analysis, Entropy, and Hurst Exponent. The list of temporal techniques is not exhaustive, but rather a representative synopsis to ease and promote their incorporation in STS analysis.

We aim to provide researchers with a checklist to choose which technique is suitable for their analysis. This checklist is based on four main attributes: (i) the function of each technique, (ii) their requirements, (iii) the types of research questions they can answer, and (iv) the data visualization options they offer. These attributes are summarized in Table 1 for each technique, and discussed in more detail below. Examples of findings from previous research are also included under each technique, to illustrate possible results one can get from the analysis, and stimulate researchers to think of possible ways through which interventions, training designs, or system structures can be developed or incorporated in STS. Appendix A includes a table of available software and availability that can further assist in choosing and carrying out these analyses.

3.3 | Lag sequential analysis (LSA)

LSA (Bakeman & Quera, 2011; Quera, 2018) can be used to determine whether a certain event is followed by another one

TABLE 1 Overview of temporal interaction analysis techniques

Analysis technique	Function	Requirements	Types of research questions and dimension of temporality addressed	Visualizations technique(s)
Lag sequential analysis	Detect patterns by identifying whether, based on predefined pattern dyads, one event follows another more often than by chance	Codes for different events/behaviors Event timestamp (ordinal and/or interval) specified pattern of interest (predefined *criterion* and *target* event)	Explore how patterns of interest evolve through interaction (*sequence*) Model patterns that are present during a phase or across different phases (*polyphony*) Compare patterns of interest across systems or situations (*timing*)	Graph/chart with prominent sequential dyads, temporal Gantt charts (CAT)
T-pattern analysis	Detect patterns by identifying whether two or more events occur sequentially more often than by chance	Codes for different events/behaviors Event timestamp (interval) Pattern occurrence threshold	Explore the intensity or complexity at which patterns evolve (*rhythm*) Model how patterns are entrained to others (*sequence*) Compare pattern complexity across systems or situations (*timing*)	Clustering diagrams or other interactive visualizations
Relational event modeling	Detect patterns of actor-based actions by identifying whether two or more events occur sequentially more often than by chance	Codes for Sender-Receiver Event timestamp (ordinal and/or interval) Specified SSSs (predefined relational event structures of sender-receiver)	Explore how the structural patterns of activities within a system can affect or predict the presence of these or other activities in the future (*polyphony*) Model the sequences of events that best explain a data set (*sequence*) Compare sequences of events across systems or situations (*timing*)	Plots of parameter estimates (and 95% confidence intervals); network structure visualizations
Recurrence analysis	Identify recurrence of an event and the formation of patterns within a time series	Codes for different events/behaviors Numerical representation of each code Event timestamp (interval) Specification of window size for higher temporal-resolution analysis	Explore the complexity of recurrent structures (*rhythm*) Model the cycles of pattern repetition within a time series (*timing*) Compare the recurrence of events across different time series (*timing*)	Recurrence plots (recurrent points are marked black in plot. Formed diagonals off the main diagonal represent patterns)
Phase space analysis	Identify recurrence of an event and the formation of patterns within a time series	Definition of categorical variables of interest Codes for each variable Variables' timestamp (ordinal/interval, to ensure that variables are presented simultaneously)	Explore how actors move across states (*rhythm*) Model the trajectory of a system from state to state (*sequence*) Compare trajectories across different time series (*timing*)	Phase space grids; State space grids

TABLE 1 (Continued)

Analysis technique	Function	Requirements	Types of research questions and dimension of temporality addressed	Visualizations technique(s)
Entropy	Identifies regularities in a time series	Codes for different events/behaviors Numerical representation of each code Event timestamp (interval) Specification of window size for higher temporal-resolution analysis	Identify and model phase transitions within a time series (*rhythm*) Compare phase transitions across different time series (*timing*)	Sliding windowed entropy graph, with entropy local maxima and local minima
Hurst Exponent	Identify the pattern of a time series	Codes for different events/behaviors Numerical representation of each code Event timestamp (interval)	Explore the auto-correlation of points within a time series (*rhythm*) Identify the presence and direction (persistence-positive vs. anitpersistence-negative) of long-range correlation in a system (*polyphony*) Model/Compare fractality across different levels (*timing*)	Moving windowed hurst graph, with local maxima and local minima

significantly more or less often than expected. The definition and coding of "event" derives from either theoretical or practical standpoints, and can be a verbal or nonverbal data point, spanning from single-word utterances or simple gestures, to more complicated behaviors or meaningful utterances (e.g., phrases, sentences, general description of behaviors or situations).

The *requirements* of LSA are, first, the development of codes (nominal variables) reflecting different events or behaviors that occur in the performance episode. Depending on the theoretical needs of the research, these codes may differ in nature, spanning from simple communication behaviors, to more theoretical complex behaviors such as behaviors related to implicit or explicit coordination patterns (Kolbe et al., 2014). A review of communication coding schemes by Brauner et al. (2018) presents various types of such coding schemes. Although LSA is mostly applied to communication structures, codes may also reflect actions on physical or technological interfaces.

A second important requirement of LSA is the timestamp of each coded event, that can be of either ordinal (only order of events known) or interval (exact time at which each event occurred) nature. The timestamps of the events are needed in order for the events to be coupled under dyadic patterns of sequential events. Based on its timestamp, an event is defined as "criterion event," referring to the first occurring event in the sequence, or as "target event," referring to one directly following the former. The relation between criterion and target events is assessed at specific serial positions called "lags"; that is, transition points from one event to the next. They can be more or less complicated, spanning from first-order transitions assessing one event directly followed by the next (Lag 1), or more complicated sequences assessing second-order transitions with one event followed by the second-to-next (Lag 2), and so on (see Figure 1 for illustration). Multiple lags can also be tested to identify significant, nonrandom chains of events. LSA requires that the patterns of interest (dyadic combinations of different criterion and target events) are specified.

The types of *research questions* that can be answered with LSA can help examine different dimensions of temporality, for example by focusing on exploring how patterns of interest evolve through interaction (sequence), modeling patterns that are present during a phase or across different phases (polyphony), or comparing patterns of interest across systems or situations (timing). An interesting example of the use of LSA in healthcare teams is the work of Kolbe et al. (2014) who found that the order of events (relating to implicit and explicit coordination behaviors) are related to performance, with higher performance teams showing significantly more behaviors of implicit coordination patterns (behaviors that facilitate action) followed by behaviors of explicit coordination patterns (behaviors coordinating joint actions) as compared to lower performing teams. These findings are valuable to understanding how self-organization unfolds in successful systems, and inform design of interventions that can help in the promotion of such processes.

Even though LSA offers valuable insights on the temporal unfolding of communication between agents in a system, one practical

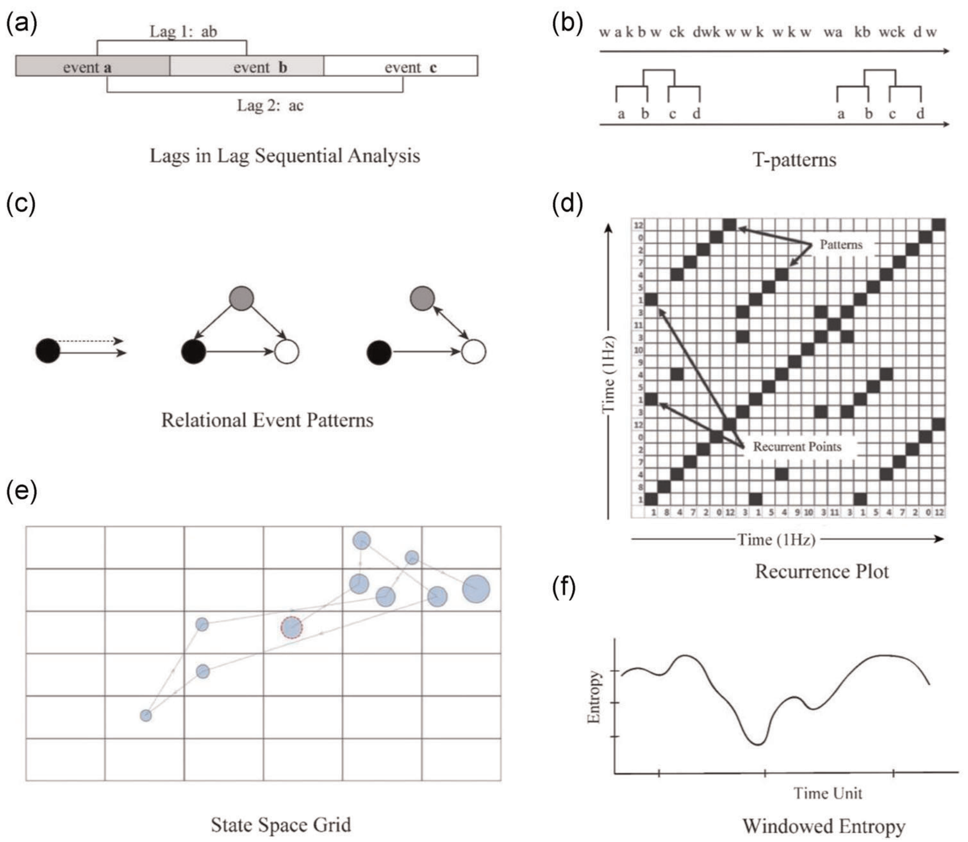

FIGURE 1 Example illustrations of temporal interaction analysis techniques. Examples of: (a) Lags in lag-sequential analysis: events a, b, and c, combined using different Lags (1, 2); in Lag 1, event a is coupled with its directly adjacent event b; in Lag 2, event a is coupled with the second-to-next event c. (b) T-Pattern analysis: events at different time intervals (top line), broken into separate complex patterns depending on their temporal proximity (Magnusson, 2000). (c) Relational events in relational event modeling: inertia, triadic closure, and preferential attachment. Dots represent actors, arrows represent direction of action, straight line indicates future action, dashed line indicates prior action. For more examples see (Schecter et al., 2018). (d) Recurrence plot (Gorman et al., 2019). (e) State Space Grid (Meinecke et al., 2019). (f) Simplified illustration of windowed entropy: entropy unraveling over a time series

limitation is its boundary concerning the complexity of sequences analysed. LSA is limited to the analysis of dyadic utterances that are immediately adjacent to one another (lag 1), or other sequential pairs (lag 2, 3, and so on), thus limiting researchers from capturing and understanding more complex patterns of interaction between different agents that may span longer sequences of utterances.

3.4 | T-pattern analysis

T-pattern analysis was developed to detect recurring sequences of temporal patterns of behavior, called T-patterns, which would be undetectable without the implementation of necessary algorithmic principles (Magnusson, 2000, 2018). A T-pattern is comprised of a criterion and a target event, and is characterized as a T-pattern if it falls within a time-dependent “critical interval.” This critical interval defines the longest possible time-interval within which a criterion is followed by a target more often than expected by chance, and is determined by two aspects: self-similarity and transition symmetry. Self-similarity refers to the hierarchical nature of these patterns, where, based on the timing at which communication utterances occur, simple patterns can be merged into larger ones, higher in the hierarchy, with which they share parts of their structure. Transition symmetry refers to similarity between patterns at different locations in time and space, creating a sequential presentation of utterances, that are of fixed order and nonrandom temporal spacing. Based on these aspects, the software THEME, developed for the identification of T-patterns, can detect if smaller patterns (*ab*) are part of larger patterns (*abcd*).

The *requirements* of T-pattern analysis entail a process of coding events similar to LSA. These codes are referred to as “event-types” and may be simple or complex communication data (a word or sentence of specific meaning), or may also reflect more contextual or machine-related activities (e.g., specific actions taken with an interface). Each event-type has a beginning (and optionally an end) that can be modeled into THEME. All event types should have a timestamp of interval scale, spanning from a few milliseconds to days (Magnusson, 2018). Depending on the needs of the research, more parameters can be entered in THEME, such as the actor who initiated each coded action.

T-pattern analysis has been used to study various different types of human and animal behaviors (for a review on applications of T-pattern analysis see Casarrubea et al., 2015). *Research questions* related to rhythm, sequence, or timing can be explored through this analysis. For example, one can use T-pattern analysis to compare pattern complexity across systems or situations (timing). Research employing T-pattern analysis suggests that higher-performing crews show less complex, shorter and fewer patterns when responding to a crisis than lower performing teams (Stachowski et al., 2009). Also, team effectiveness has been associated to patterns that are more stable in complexity during early phases of swift-starting (Zijlstra et al., 2012). These are examples of how T-pattern analysis can help spot the “right” moment and way for change to occur in the behavior of a system, informing the design of system structures that can assist in the manifestation of such processes.

It is important to mention that T-system analysis is a bottom-up approach tailored toward the detection and analysis of patterns, rather than concerned with the relations between recurrent entities as LSA does, adding the advantage of exploratory research to detect patterns that have not yet been discussed in theoretical constructs. The advantage of using this method of pattern detection and mapping is its unbiased exploratory approach. Even though theory on communication can offer indications on which patterns are expected in the data, it can omit other patterns that are nonetheless important in indicating core structures in communication (Magnusson, 2000). Despite its possibility to assist, T-pattern analysis mayyield Type 1 errors of exploratory analyses.

3.5 | Relational event modeling

Relational event modeling is based on the premise that the relationship of the actors within a network is based on their series of relational events (Butts, 2008; Butts & Marcum, 2017). Any relational event (*e*) consists of a sender *s(e)*, a receiver *r(e)* and a timestamp *t(e)*. By modeling all relational events as they unfold over time, one can capture a long sequence of events (E), comprising the entire interaction process.

Relational event modeling has three main *requirements*, starting with a coding process of labeling the actors of a performance episode and their function as senders or receivers during each action.[1] The inclusion of each action's timestamp is also necessary. The timestamp can be of interval or ordinal nature, although in the latter case fidelity is lost with regard to the rate at which actions occur (Butts, 2008). The third requirement is constructing Sequential Structural Signatures (SSSs), referring to predefined relational event structures that examine various actor-based relationships. They are used to statistically assess the likelihood of a relational event to occur based on preceding relational events. R packages such as relevent (Butts, 2008) or informR (Marcum & Butts, 2015) include already constructed SSSs that reflect a wide range of social processes, such as the persistence or order of action, the exchanges of information within triads of actors, or conversational dynamics and preferential attachment (Butts & Marcum, 2017). Different models can be built, incorporating isolated or combined SSSs. By assessing the goodness-of-fit of each model, one can capture social processes that best explain the data set. SSSs, and the ability to combine these under different models, enable the application of relational event modeling in various social contexts of different theoretical base. For a tutorial on its application see Butts and Marcum (2017).

Relational event modeling can be used to answer *research questions* related to exploring the effect of different social processes on a system's structure. Researchers can model the sequences of events that best explain a data set (sequence), or compare sequences of events across systems or situations (timing). For example, the social process of inertia, characterized by a higher likelihood for an actor's past contact to remain their future contact, has been associated with higher stability and coordination in routine situations (Schecter et al., 2018), but also with poor teamwork during emergency flight situations (David & Schraagen, 2018) and critical situations in pediatric cardiac surgery (Van den Oever & Schraagen, 2021) Further, Relational event modeling is one of the few processes that can assess polyphony within a data set; that is, researchers are able to investigate how the structural patterns of activities within a system can affect the presence of these or other activities in the future. Hierarchical extensions of relational event modeling (e.g., see, DuBois et al., 2013) further enable pooling across multiple information sequences, an attribute useful for investigation of different groups or investigation of covariates within these groups.

3.6 | Recurrence analysis

Recurrence analysis is usually used to assess whether interval data points within a nonlinear time series are recurrent or random (Webber & Zbilut, 1994). Such data points may, for example, be physiological measures of brainwave activity or heart rate (Strang et al., 2014). While such an analysis refers to data points of regular time intervals, variations of the recurrence analysis can also be applied to discrete interaction sequences of ordinal spacing, to identify deterministic sequences of patterned events in a performance episode (Gorman et al., 2012, 2019). For a discrete recurrence analysis, *requirements* include a set of codes representing events or actions, with each code associated with a number. Each code should have a temporal timestamp indicating its beginning and ending. For every second that the event occurred in the performance episode, the respective event number is plotted on the recurrence plot. For example, to assess speech patterns, each agent in a system can be represented by a different number, and each speech activity can be modeled on the recurrence plot using the agent's number for as long as the agent speaks, followed by the next speaking activity, and so on. For a recurrent analysis, determining a *window size* (windowed recurrence analysis) enables a higher temporal-resolution of analysis, enabling recurrent patterns to be researched more thoroughly within

[1]Variations of REM may incorporate the weight of actions (Brandes et al., 2009) or different types of receivers (Vu et al., 2015) in the coding process.

each window and compared from window to window. Window size is determined by the number of data points that each window includes. Small window sizes focus on small-scale recurrences and yield higher time-resolution patterns, while long size windows focus on long-scale recurrences and yield lower time-resolution patterns. A window size should reflect the pacing of system interaction changes, and so the concept of event pacing (defined earlier as the speed at which activities occur) is an important consideration when determining window sizes.

Recurrence analysis has its basis on the recurrence plot, which represents a matrix of a time series, in which repetition of a pattern is marked black on the plot, and sequences of repetitive patterns for diagonals that can be detected directly on it. The recurrence plot is a symmetrical matrix plotting the time series of length N ($N \times N$), meaning that the diagonal running through the middle (bottom left to upper right corner in Figure 1) is blackened as a reflection of the time series being plotted against itself. Its symmetric nature is also the reason why the same patterns are reflected on the upper left and bottom right part of the plot. Various quantifications of the recurrence plot can be used to assist in its interpretation and further analysis. For example, *determinism* (%DET) is a metric that calculates the percentage of formed diagonals. Based on DET, a time-series is considered completely deterministic when a sequence of events (e.g., A-B-C) always repeats (in which case we have a homogenous plot of DET = 100). Lower DET values represent higher percentage of random sequences and lower percentage of deterministic ones. Other metrics are *linemax* (LMAX), a measure of stability quantifying the length of the longest diagonal in the plot, or *entropy* (discussed in Section 3.8). For more quantification metrics see Webber and Zbilut (2005).

Recurrence analysis can be used to assess a variety of *research questions* both within and across different time-series, on social phenomena such as speech activity. One can explore the complexity of recurrent structures in turn taking, model the cycles of pattern repetition within a time series, or compare the recurrence of events across different time series. In combination with other quantification measures, other research questions can also be addressed. For example, Gorman et al. (2019) modeled a turn-taking time series of who was talking at each second of a performance episode on an recurrence plot, and used %DET to determine communication reorganization in response to perturbations. Results indicated that coordination of reorganization process is a cognitive skill that differs between experienced and novice teams, and can be measured and tracked. For a review on recurrence analysis and examples in team research see Knight et al. (2016).

3.7 | Phase space analysis

Phase space analysis includes plotting a system's *state space* to understand the structural characteristics of a time series (Hollenstein, 2007). As a system functions, it presents some kind of variability, which means that it moves through different states that comprise a state space. A system's state space includes attractors, defined as states that reoccur more often, and repellors, states reoccurring less often. The movement from one state to another creates a traceable path trajectory. A system also presents *phase transitions*, when it moves out of its usual trajectory, presenting new dynamics before stabilizing on a new phase (e.g., team presenting new patterns when a membership changes). Phase space analysis can be plotted on a *state space grid*, which visualizes the trajectory of the system and provides various quantifications for the content and structure of the trajectory (Meinecke et al., 2019).

Requirements for a phase space analysis are the definition of at least two categorical variables (i.e., dimensions) that characterize the state space. The variables plotted on the x and y axis may be different depending on the aim of the research. For example, the system's agents can be plotted on the x axis and the various actions or events on the y axis. It is important that the variables are presented at the same point in time, as each cell of the grid assumes a simultaneous coexistence of the two variables. Therefore, relative nominal codes representing events, actions, agents or other variables of interest within a time series need to be coded. An ordinal or interval timestamp should accompany each variable, ensuring the proper association between the two in the state space grid. Similar to Recurrence analysis, window size can also be determined, and different quantifications can be used for the interpretation of the state space grid in terms of content or structure of the trajectories, such *total cell transitions* (number of visits from one cell to another), or *entropy*.

Phase space analysis can help address *research questions* related to exploring group norms within a times series, or comparing group norms across time-series. For example, one can explore how actors move across states (rhythm), or research the appearance of pattern sequences by modeling the trajectory of a system from state to state (sequence). One can also compare trajectories across different time series (timing), thus gaining insights on how different teams exhibit transitioning across states.

3.8 | Entropy

Entropy provides a means of detecting randomness, or uncertainty within a time series (Pincus et al., 1991). Entropy is expressed in bits and different systems have different amounts of entropy depending on the number of possible states in each system, that is, $\log_2(x)$, where x is the number of possible states (Stevens, 2012). An increase in entropy reflects a higher level of disorder in data points (and thus in the system's behavior), marking a sequence as more irregular. Sliding windowed entropy can capture how a system moves from state to state by detecting regularities in sequences within each window. Within nonlinear dynamical systems theory, entropy is considered to be generated by the system as this changes its behavior over a time series. Based on the coded event, that being defined as a verbal or physiological behavior, peaks in entropy may indicate phase or other state transitions. By applying smoothing in siding windowed entropy, the robustness of peaks increases (see, Wiltshire et al., 2018). An example of how entropy can be modeled is provided in Figure 1. Entropy needs at least 1000 data values for a robust analysis to be carried out.

Requirements for estimating entropy are similar to the requirements of recurrence analysis (coding, number associated to each code, specification of window size). The *research questions* addressed with entropy are related to modeling phase transitions within a time series, or comparing transitions across many time series. The constraints of a system begin collapse when a system goes through a phase transition, showing higher entropy (Kugler & Turvey, 1987; Wiltshire et al., 2018). Entropy can also be used to compare regularities across different time series. For example, mapping entropy peaks onto performance episodes involving environmental changes (transitioning from task to task) reveals the underlying system structures that lead to higher system effectiveness, and can also be associated to cognitive stability and flexibility (Stevens, 2012).

3.9 | Hurst exponent

Hurst exponent (*H*), is a measure of autocorrelation and fractality in a time series (DePetrillo et al., 1999). It ranges on an arbitrary scale of 0–1, and reflects the extent to which points in a time series are correlated to each other. An $H = 0.5$ indicates a random time-series where points are not correlated to one another. $H > 0.5$ indicates a *persistent* process of positive correlations between points, where an upward moving point is followed by another upward moving point and usually interpreted as the tendency of systems to show autocorrelation or corrective behavior. $H < 0.5$ reflects an *anti-persistent* process, where points are negatively correlated, meaning that one point moving upward is more likely to be followed by a downward one. The main *requirement* for estimating *H* is a data set of interval datapoints in a time series. Different methods exist for its estimation, such as rescaled range (*R*/*S*) analysis, or variance time analysis (for details on the estimation methods see Kirichenko et al., 2018). An example application of Hurst exponent on team coordination using a continuous time series of electroencephalography signals can be found in Likens et al. (2014). For application on ordinal communication data see Gorman and Cooke (2010). The *research questions* that *H* exponent can address relate to the extent of self-similarity across a time series of different hierarchical levels, as well as in modeling or compare fractality across different levels.

Studying STS, especially in closed settings where recording is possible, such as aviation cockpits or surgical rooms, offers the opportunity for gathering the fine-grained data required for these analyses, such as full transcripts from black boxes or voyage data recorder, or physiological data using sociometric badges (Kim et al., 2012). Even in STS of organizational units with less monitoring, video or audio-based measurements enable the continuous procurement of team dynamics as these unfold within a performance event.

Most analysis techniques so far require transcribing and manually coding communication before analysis, although some attempts are being made at incorporating the automatic attainment of meaningful information on team measures through machine learning (e.g., Bonito & Keyton, 2018). Coding can be performed at different levels of granularity, depending on the aim of the research, the data available and the detail associated with that data, as well as the methodological tools at hand. For example, one may focus on micro-behaviors based on coding of single seconds within a time series, such as silences or laughter, whereas others may instead code macro-behaviors that span over several minutes or hours. The coding process and guidelines for such analyses is outside the scope of this study. For a review on existing coding schemes see Brauner et al. (2018), and for guidelines focused on developing new coding schemes see Waller and Kaplan (2018).

To perform the analyses, specialized software has been developed for some, while statistical R packages are also readily available for application. Use of specialized software increases the validity of the analyses in terms of meeting the assumptions they dictate (Connor et al., 2009). Generic software for coding and analysis such as Observer-XT (Noldus et al., 2000), Interact (Mangold, 2020), or CAT (Klonek et al., 2020) can also lead to high quality analysis by easing the coding process and prompting the attention of researchers to specific decisions that need to be made regarding the analysis they choose. A full list of software is included in the appendix.

4 | SUMMARY AND CONCLUSIONS

The purpose of the present paper was to promote the incorporation of temporal interaction analysis techniques in sociotechnical systems research. It is clear that different ergonomics methods may be applied to different levels of analysis within a system's hierarchy, focusing on processes from immediate interaction, to higher, macro-level processes that occur across multilayered systems. However, the methods used for the analysis of complex systems often take a static approach to system operation. We argue that studying dimensions of temporality at a micro-level of analysis can further assist and deepen our understanding of STS systems by revealing temporal interaction patterns that would otherwise remain undetectable. The thorough investigation opportunities offered by such techniques can help understand and predict system behavior.

We presented an overview of various temporal interaction analysis techniques derived from complexity science, complex adaptive systems and nonlinear dynamical systems theory, and created a table of properties that can ease their inclusion in STS research. These techniques aim to increase the fidelity of research with respect to the exact processes that make-up relationships between agents, functions, and the development and change of system boundaries over time. Within the techniques presented, it is important to understand how investigation is not necessarily limited to conversational variables, but can also be applied to any type of ordinal or continuous data, such as human-interface interaction behaviors, physiological measures, or psychological states (Gorman et al., 2019) that can help in the identification of important processes and states and how these change over time.

4.1 | Limitations and future directions

The current review does not constitute an exhaustive list of temporal techniques, but rather a representative synopsis of those included in existing reviews from learning and team communication science (Herndon & Lewis, 2015; Klonek et al., 2019; Lehmann-Willenbrock & Allen, 2018), complex adaptive systems (McComb & Kennedy, 2020), and nonlinear dynamical systems (Ramos-Villagrasa et al., 2018), and which do not suffer from limitations associated with linear approaches assuming homogeneity of data (Connor et al., 2009; Leenders et al., 2016). It is possible that other techniques from disciplines such as computer science can also account as suitable temporal interaction analysis techniques. Attempts to bridge social and computer sciences have already been made (see, Lehmann-Willenbrock et al., 2017), and future research should consider to what extent the analysis of temporality and complex interaction patterns is included in such techniques.

Further, the toolbox of techniques provided in the current article is descriptive and explanatory in nature. The main concepts of each technique are portrayed with some examples that can assist in guiding their application in complex systems. Future research on the actual application and exploration of these techniques can improve our understanding of the extent to which they complement other methods and analyses. More specifically, these techniques are very useful in explaining "when" or "how" systems change, but provide a challenge to the interpretation of the results in terms of "what" or "why" processes change the way that they do. For a holistic understanding of a system and the creation of an all-inclusive intervention, the combination of micro-level temporal techniques with other methodologies can ease the holistic interpretation of results yielded from the analysis. A combination with techniques and methodologies that investigate "what" or "why" aspects in more detail can assist in the design and implementation of interventions rooted on exact beneficial or destructive processes that emerge as systems function.

We therefore propose that the temporal techniques discussed need not necessarily be applied in isolation, but can also be combined with other models higher in the hierarchy. Some methodologies already attempt to combine a meso-level of analysis, focusing on the interaction of different system layers, with a micro-level temporal investigation of interaction changes across these system layers. One example is the layered dynamics approach (Gorman et al., 2019). Another useful and insightful approach that combines different levels of analysis is many model thinking, and involves using multiple different models to research the same system or complex problem. Many model thinking is a leading example of how combining approaches of different foci and detail can help build better systems (Page, 2016).

For instance, Salmon and Read (2019) applied many models thinking, combining meso and macro level approaches. They included Cognitive Work Analysis, EAST, AcciMaps, STAMP, and a computational model of systems dynamics to investigate the issue of road trauma. Insights from each model were combined to develop a holistic cluster of strategies that can be used to prevent road trauma. In the many model thinking analysis, AcciMaps were used to analyse the problem, followed by an break-down of the system using STAMP and CWA, the analysis of behaviors within specific scenarios with EAST, and ending with a design of interventions informed by the findings, which was modeled using systems dynamics. In their discussion, Salmon et al. pointed out how a micro-level approach, absent in their analysis, could be implemented within the investigation to further inform intervention design. We encourage the future application of a many model thinking to a complex STS problem, combining higher-level methods with those mapping moment-by-moment interaction processes. Such an application will enable a detailed investigation of how findings with varied degrees of detail, and their implications on intervention design for complex STS are complemented and enriched.

In conclusion, the application of the temporal interaction analysis techniques presented in this article, either in isolation or as complementary to other methods, enables a thorough analysis of how processes emerge and fluctuate as systems develop and self-organize. These techniques can be used to enhance and broaden the expansion and applicability of Human Factors research across different domains and complex systems.

ORCID

Lida Z. David http://orcid.org/0000-0001-8799-6952

Jan Maarten Schraagen https://orcid.org/0000-0003-4467-7286

REFERENCES

Arrow, H., Poole, M. S., Henry, K. B., Wheelan, S., & Moreland, R. (2004). Time, change, and development: The temporal perspective on groups. *Small Group Research*, *35*(1), 73–105. https://doi.org/10.1177/1046496403259757

Arthur, W., Edwards, B. D., Bell, S. T., Villado, A. J., & Bennett, W. (2005). Team task analysis: Identifying tasks and jobs that are team based. *Human Factors*, *47*(3), 654–669. https://doi.org/10.1518/001872005774860087

Ashby, W. R. (1956). *An introduction to cybernetics*. Chapman & Hall Ltd.

Bakeman, R., & Quera, V. (2011). *Sequential analysis and observational methods for the behavioral sciences*. Cambridge University Press. https://doi.org/10.1017/CBO9781139017343

Barth, S., Schraagen, J. M., & Schmettow, M. (2015). Network measures for characterising team adaptation processes. *Ergonomics*, *58*(8), 1287–1302. https://doi.org/10.1080/00140139.2015.1009951

Bartunek, J. M., & Woodman, R. W. (2015). Beyond Lewin: Toward a temporal approximation of organization development and change. *Annual Review of Organizational Psychology and Organizational Behavior*, *2*(1), 157–182. https://doi.org/10.1146/annurev-orgpsych-032414-111353

Bonito, J. A., & Keyton, J. (2018). Introduction to machine learning: Teaching computers to code group interaction data. In E. Brauner, M. Boos, & M. Kolbe (Eds.), *The Cambridge handbook of group interaction analysis* (pp. 387–404). Cambridge University Press. https://doi.org/10.1017/9781316286302.020

Bowers, C. A., Baker, D. P., & Salas, E. (1994). Measuring the importance of teamwork: The reliability and validity of job/task analysis indices for team-training design. *Military Psychology*, *6*(4), 205–214. https://doi.org/10.1207/s15327876mp0604_1

Brandes, U., Lerner, J., & Snijders, T. A. B. (2009). Networks evolving step by step: Statistical analysis of dyadic event data. *Proceedings of the*

2009 International Conference on Advances in Social Network Analysis and Mining, ASONAM 2009, pp. 200–205. https://doi.org/10.1109/ASONAM.2009.28

Brauner, E., Boos, M., & Kolbe, M. (Eds.). (2018). Coding schemes for interaction research, *The Cambridge handbook of group interaction analysis* (pp. 419–638). Cambridge University Press.

Butts, C. T., & Marcum, C. S. (2017). A relational event approach to modeling behavioral dynamics. In A. Pilny, & M. S. Poole (Eds.), *Group processes: Data-driven computational approaches* (pp. 51–92).

Butts, C. T. (2008). A relational event framework for social action. *Sociological Methodology*, *38*(1), 155–200. https://doi.org/10.1111/j.1467-9531.2008.00203.x

Cannon-Bowers, J. A., Salas, E., & Converse, S. (1993). Shared mental models in expert team decision making. In N. J. Castellan, Jr. (Ed.), *Individual and group decision making: Current issues* (pp. 221–246). Lawrence Erlbaum Associates, Inc.

Casarrubea, M., Jonsson, G. K., Faulisi, F., Sorbera, F., Di Giovanni, G., Benigno, A., Crescimanno, G., & Magnusson, M. S. (2015). T-pattern analysis for the study of temporal structure of animal and human behavior: A comprehensive review. *Journal of Neuroscience Methods*, *239*, 34–46. https://doi.org/10.1016/j.jneumeth.2014.09.024

Clegg, C. W. (2000). Sociotechnical principles for system design. *Applied Ergonomics*, *31*(5), 463–477. https://doi.org/10.1016/S0003-6870(00)00009-0

Collins, C. G., Gibson, C. B., Quigley, N. R., & Parker, S. K. (2016). Unpacking team dynamics with growth modeling: An approach to test, refine, and integrate theory. *Organizational Psychology Review*, *6*(1), 63–91. https://doi.org/10.1177/2041386614561249

Connor, M., Fletcher, I., & Salmon, P. (2009). The analysis of verbal interaction sequences in dyadic clinical communication: A review of methods. *Patient Education and Counseling*, *75*(2), 169–177. https://doi.org/10.1016/j.pec.2008.10.006

Cooke, N. J., Gorman, J. C., Myers, C. W., & Duran, J. L. (2013). Interactive team cognition. *Cognitive science*, *37*(2), 255–285. https://doi.org/10.1111/cogs.12009

David, L. Z., & Schraagen, J. M. (2018). Analysing communication dynamics at the transaction level: The case of Air France Flight 447. *Cognition, Technology and Work*, *20*(4), 637–649. https://doi.org/10.1007/s10111-018-0506-y

DePetrillo, P. B., Speers, D., & Ruttimann, U. E. (1999). Determining the Hurst exponent of fractal time series and its application to electrocardiographic analysis. *Computers in Biology and Medicine*, *29*(6), 393–406. https://doi.org/10.1016/S0010-4825(99)00018-9

DuBois, C., Butts, C. T., McFarland, D., & Smyth, P. (2013). Hierarchical models for relational event sequences. *Journal of Mathematical Psychology*, *57*(6), 297–309. https://doi.org/10.1016/j.jmp.2013.04.001

Eason, K. (2014). Afterword: The past, present and future of sociotechnical systems theory. *Applied Ergonomics*, *45*(2), 213–220. https://doi.org/10.1016/j.apergo.2013.09.017

Foster, C. J., Plant, K. L., & Stanton, N. A. (2020). A Delphi study of human factors methods for the evaluation of adaptation in safety-related organisations. *Safety Science*, *131*, 104933. https://doi.org/10.1016/j.ssci.2020.104933

Fransen, A. F., van de Ven, J., Schuit, E., van Tetering, A. A. C., Mol, B. W., & Oei, S. G. (2017). Simulation-based team training for multi-professional obstetric care teams to improve patient outcome: A multicentre, cluster randomised controlled trial. *BJOG*, *124*(4), 641–650. https://doi.org/10.1111/1471-0528.14369

Gorman, J. C. (2014). Team coordination and dynamics. *Current Directions in Psychological Science*, *23*(5), 355–360. https://doi.org/10.1177/0963721414545215

Gorman, J. C., & Cooke, N. J. (2010). Team coordination dynamics. *Nonlinear dynamics, psychology, and life sciences*, *14*(3), 265–289.

Gorman, J. C., Demir, M., Cooke, N. J., & Grimm, D. A. (2019). Evaluating sociotechnical dynamics in a simulated remotely-piloted aircraft system: A layered dynamics approach. *Ergonomics*, *62*(5), 629–643. https://doi.org/10.1080/00140139.2018.1557750

Gorman, J. C., Dunbar, T. A., Grimm, D., & Gipson, C. L. (2017). Understanding and modeling teams as dynamical systems. *Frontiers in Psychology*, *8*(1053), 1053. https://doi.org/10.3389/fpsyg.2017.01053

Gorman, J. C., Grimm, D. A., Stevens, R. H., Galloway, T., Willemsen-Dunlap, A. M., & Halpin, D. J. (2019). Measuring real-time team cognition during team training. *Human Factors*, *62*(5), 825–860. https://doi.org/10.1177/0018720819852791

Gorman, J. C., Hessler, E. E., Amazeen, P. G., Cooke, N. J., & Shope, S. M. (2012). Dynamical analysis in real time: Detecting perturbations to team communication. *Ergonomics*, *55*(8), 825–839. https://doi.org/10.1080/00140139.2012.679317

Grote, G., Weyer, J., & Stanton, N. A. (2014). Beyond human-centred automation—Concepts for human-machine interaction in multi-layered networks. *Ergonomics*, *57*(3), 289–294. https://doi.org/10.1080/00140139.2014.890748

Hendrick, H. W., & Kleiner, B. M. (2002). *Macroergonomics*. Lawrence Erlbaum Associates Publishers. https://doi.org/10.1201/b12477

Herndon, B., & Lewis, K. (2015). Applying sequence methods to the study of team temporal dynamics. *Organizational Psychology Review*, *5*(4), 318–332. https://doi.org/10.1177/2041386614538276

Hollenstein, T. (2007). State space grids: Analyzing dynamics across development. *International Journal of Behavioral Development*, *31*(4), 384–396. https://doi.org/10.1177/0165025407077765

Hollnagel, E. (2012). *FRAM: The functional resonance analysis method: Modelling complex socio-technical systems* (1st ed.). Routledge. https://doi.org/10.1201/9781315255071

Hollnagel, E., & Goteman, Ö. (2004, January 1). The functional resonance accident model. *Proceedings of Cognitive System Engineering in Process Plant*.

Hollnagel, E., & Sundström, G. (2006). States of resilience. In E. Hollnagel, D. D. Woods, & N. Leveson (Eds.), *Resilience engineering: Concepts and precepts* (p. 397). Ashgate.

Kim, T., McFee, E., Olguin, D. O., Waber, B., & Pentland, A. S. (2012). Sociometric badges: Using sensor technology to capture new forms of collaboration. *Journal of Organizational Behavior*, *33*(3), 412–427. https://doi.org/10.1002/job.1776

Kirichenko, L., Radivilova, T., & Bulakh, V. (2018). Generalized approach to hurst exponent estimating by time series. *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, *8*(1), 28–31. https://doi.org/10.5604/01.3001.0010.8639

Klein, G. A., Calderwood, R., & MacGregor, D. (1989). Critical decision method for eliciting knowledge. *IEEE Transactions on Systems, Man and Cybernetics*, *19*(3), 462–472. https://doi.org/10.1109/21.31053

Klonek, F., Gerpott, F. H. G., Lehmann-Willenbrock, N., & Parker, S. K. (2019). Time to go wild: How to conceptualize and measure process dynamics in real teams with high-resolution. *Organizational Psychology Review*, *9*(4), 245–275. https://doi.org/10.1177/2041386619886674

Klonek, F., Meinecke, A. L., Hay, G., & Parker, S. K. (2020). Capturing team dynamics in the wild: The communication analysis tool. *Small Group Research*, *51*(3), 303–341. https://doi.org/10.1177/1046496420904126

Knight, A. P., Kennedy, D. M., & Mccomb, S. A. (2016). Using recurrence analysis to examine group dynamics. *Group Dynamics: Theory, Research, and Practice*, *20*(3), 223–241. https://doi.org/10.1037/gdn0000046

Kolbe, M., Grote, G., Waller, M. J., Wacker, J., Grande, B., Burtscher, M. J., & Spahn, D. R. (2014). Monitoring and talking to the room: Autochthonous coordination patterns in team interaction and performance. *Journal of Applied Psychology*, *99*(6), 1254–1267. https://doi.org/10.1037/a0037877

Koudenburg, N., Postmes, T., & Gordijn, E. H. (2017). Beyond content of conversation: The role of conversational form in the emergence and regulation of social structure. *Personality and Social Psychology Review*, *21*(1), 50–71. https://doi.org/10.1177/1088868315626022

Kugler, P. N., & Turvey, M. T. (1987). *Information, natural law, and the self-assembly of rhythmic movement*. Lawrence Erlbaum Associates, Inc.

Lavelle, M., Reedy, G. B., Cross, S., Jaye, P., Simpson, T., & Anderson, J. E. (2020). An evidence based framework for the temporal observational analysis of teamwork in healthcare settings. *Applied Ergonomics*, *82*, 102915. https://doi.org/10.1016/j.apergo.2019.102915

Leenders, R. T. A. J., Contractor, N. S., & DeChurch, L. A. (2016). Once upon a time: Understanding team processes as relational event networks. *Organizational Psychology Review*, *6*(1), 92–115. https://doi.org/10.1177/2041386615578312

Lehmann-Willenbrock, N., & Allen, J. A. (2018). Modeling temporal interaction dynamics in organizational settings. *Journal of Business and Psychology*, *33*(3), 325–344. https://doi.org/10.1007/s10869-017-9506-9

Lehmann-Willenbrock, N., Hung, H., & Keyton, J. (2017). New frontiers in analyzing dynamic group interactions: Bridging social and computer science. *Small Group Research*, *48*(5), 519–531. https://doi.org/10.1177/1046496417718941

Lei, Z., Waller, M. J., Hagen, J., & Kaplan, S. (2016). Team adaptiveness in dynamic contexts: Contextualizing the roles of interaction patterns and in-process planning. *Group & Organization Management*, *41*(4), 491–525. https://doi.org/10.1177/1059601115615246

Leveson, N. (2004). A new accident model for engineering safer systems. *Safety Science*, *42*(4), 237–270. https://doi.org/10.1016/S0925-7535(03)00047-X

Likens, A. D., Amazeen, P. G., Stevens, R., Galloway, T., & Gorman, J. C. (2014). Neural signatures of team coordination are revealed by multifractal analysis. *Social neuroscience*, *9*(3), 219–234. https://doi.org/10.1080/17470919.2014.882861

Magnusson, M. S. (2000). Discovering hidden time patterns in behavior: T-patterns and their detection. *Behavior Research Methods, Instruments, and Computers*, *32*(1), 93–110. https://doi.org/10.3758/BF03200792

Magnusson, M. S. (2018). Temporal patterns in interactions. In E. Brauner, M. Boos, & M. Kolbe (Eds.), *The Cambridge handbook of group interaction analysis* (pp. 323–353). Cambridge University Press. https://doi.org/10.1017/9781316286302.017

Mandelbrot, B. B. (1983). *The fractal geometry of nature*. W. H. Freeman and Co.

Mangold. (2020). *INTERACT user guide*. Mangold International GmbH (Ed.). www.mangold-international.com

Marcum, C. S., & Butts, C. T. (2015). Constructing and modifying sequence statistics for relevent using informR in R. *Journal of Statistical Software*, *64*(5), 1–36. https://doi.org/10.18637/jss.v064.i05

McComb, S., & Kennedy, D. (2020). *Computational methods to examine team communication*. Springer International Publishing. https://doi.org/10.1007/978-3-030-36159-4

Meinecke, A. L., Hemshorn de Sanchez, C. S., Lehmann-Willenbrock, N., & Buengeler, C. (2019). Using state space grids for modeling temporal team dynamics. *Frontiers in Psychology*, *10*(863), 863. https://doi.org/10.3389/fpsyg.2019.00863

Militello, L., Hutton, R., Pliske, R., Knight, B., & Klein, G. (1997). *Applied cognitive task analysis (ACTA) methodology*. p. 193.

Noldus, L. P. J. J., Trienes, R. J. H., Hendriksen, A. H. M., Jansen, H., & Jansen, R. G. (2000). The Observer Video-Pro: New software for the collection, management, and presentation of time-structured data from videotapes and digital media files. *Behavior Research Methods, Instruments, & Computers*, *32*(1), 197–206. https://doi.org/10.3758/BF03200802

Olsen, E. (2007). Evaluation of human work. In J. R. Wilson, & N. Corlett (Eds.), *Ergonomics in design: The quarterly of human factors applications* (Vol. 15, 3rd ed.). CRC Press. https://doi.org/10.1177/106480460701500211

Page, S. (2016). Many model thinking. *IEEE, Winter Simulation Conference (WSC)*.

Phelan, S. (2001). What is complexity science, really? *Emergence*, *3*(1), 120–136. https://doi.org/10.1207/S15327000EM0301_08

Pincus, S. M., Gladstone, I. M., & Ehrenkranz, R. A. (1991). A regularity statistic for medical data analysis. *Journal of Clinical Monitoring*, *7*(4), 335–345. https://doi.org/10.1007/BF01619355

Price, J. W., Applegarth, O., Vu, M., & Price, J. R. (2012). Code blue emergencies: A team task analysis and educational initiative. *Canadian Medical Education Journal*, *3*(1), e4–e20. https://doi.org/10.36834/cmej.36567

Quera, V. (2018). Analysis of interaction sequences. In E. Brauner, M. Boos, & M. Kolbe (Eds.), *The Cambridge handbook of group interaction analysis* (pp. 295–322). Cambridge University Press. https://doi.org/10.1017/9781316286302.016

Ramos-Villagrasa, P. J., Marques-Quinteiro, P., Navarro, J., & Rico, R. (2018). Teams as complex adaptive systems: Reviewing 17 years of research. *Small Group Research*, *49*(2), 135–176. https://doi.org/10.1177/1046496417713849

Salmon, P. M., & Read, G. J. M. (2019). Many model thinking in systems ergonomics: A case study in road safety. *Ergonomics*, *62*(5), 612–628. https://doi.org/10.1080/00140139.2018.1550214

Salmon, P. M., Read, G. J. M., Walker, G. H., Stevens, N. J., Hulme, A., McLean, S., & Stanton, N. A. (2020). Methodological issues in systems Human Factors and Ergonomics: Perspectives on the research–practice gap, reliability and validity, and prediction. *Human Factors and Ergonomics in Manufacturing & Service Industries*. https://doi.org/10.1002/hfm.20873

Schecter, A., Pilny, A., Leung, A., Poole, M. S., & Contractor, N. (2018). Step by step: Capturing the dynamics of work team process through relational event sequences. *Journal of Organizational Behavior*, *39*(9), 1163–1181. https://doi.org/10.1002/job.2247

Schmutz, J. B., & Eppich, W. J. (2017). Promoting learning and patient care through shared reflection: A conceptual framework for team reflexivity in health care. *Academic Medicine*, *92*(11), 1555–1563. https://doi.org/10.1097/ACM.0000000000001688

Shorrock, S., & Kirwan, B. (2002). Development and application of a human error identification tool for air traffic control. *Applied Ergonomics*, *33*(4), 319–336. https://doi.org/10.1016/S0003-6870(02)00010-8

Stachowski, A. A., Kaplan, S. A., & Waller, M. J. (2009). The benefits of flexible team interaction during crises. *Journal of Applied Psychology*, *94*(6), 1536–1543. https://doi.org/10.1037/a0016903

Stanton, N. A. (2013). Representing distributed cognition in complex systems: How a submarine returns to periscope depth. *Ergonomics*, *57*(3), 403–418. https://doi.org/10.1080/00140139.2013.772244

Stanton, N. A., Baber, C., & Harris, D. (2008). *Modelling command and control: Event analysis of systemic teamwork*. CRC Press.

Stanton, N. A., Salmon, P., Rafferty, L., Walker, G., Baber, C., & Jenkins, D. P. (2013). *Human Factors methods: A practical guide for engineering and design* (2nd ed.). Ashgate.

Stevens, R. (2012). Charting neurodynamic eddies in the temporal flows of teamwork. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *56*, 208–212. https://doi.org/10.1177/1071181312561020

Strang, A. J., Funke, G. J., Russell, S. M., Dukes, A. W., & Middendorf, M. S. (2014). Physio-behavioral coupling in a cooperative team task: Contributors and relations. *Journal of Experimental Psychology: Human Perception and Performance*, *40*, (1), 145–158. https://doi.org/10.1037/a0033125

Swain, A. D., & Guttmann, H. E. (1983). *Handbook of human-reliability analysis with emphasis on nuclear power plant applications*. Final report. https://doi.org/10.2172/5752058

Underwood, P., & Waterson, P. (2014). Systems thinking, the Swiss Cheese Model and accident analysis: A comparative systemic analysis of the Grayrigg train derailment using the ATSB, AcciMap and STAMP models. *Accident Analysis and Prevention*, *68*, 75–94. https://doi.org/10.1016/j.aap.2013.07.027

Van den Oever, F., & Schraagen, J. M. (2021). Team communication patterns in critical situations. *Journal of Cognitive Engineering and Decision Making*, *1*(15), 28–51.

Vu, D., Pattison, P., & Robins, G. (2015). Relational event models for social learning in MOOCs. *Social Networks*, *43*, 121–135. https://doi.org/10.1016/j.socnet.2015.05.001

Waller, M. J., & Kaplan, S. A. (2018). Systematic Behavioral Observation for Emergent Team Phenomena. *Organizational Research Methods*, *21*(2), 500–515. https://doi.org/10.1177/1094428116647785

Waterson, P., Robertson, M. M., Cooke, N. J., Militello, L., Roth, E., & Stanton, N. A. (2015). Defining the methodological challenges and opportunities for an effective science of sociotechnical systems and safety. *Ergonomics*, *58*(4), 565–599. https://doi.org/10.1080/00140139.2015.1015622

Webber, C. L., & Zbilut, J. (2005). Recurrence quantification analysis of nonlinear dynamical systems. In M. Riley, & G. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 26–94). Arlington, VA: National Science Foundation.

Webber, C. L., & Zbilut, J. P. (1994). Dynamical assessment of physiological systems and states using recurrence plot strategies. *Journal of Applied Physiology*, *76*(2), 965–973. https://doi.org/10.1152/jappl.1994.76.2.965

Wiltshire, T. J., Butner, J. E., & Fiore, S. M. (2018). Problem-solving phase transitions during team collaboration. *Cognitive Science*, *42*(1), 129–167. https://doi.org/10.1111/cogs.12482

Woods, D. D., Dekker, S., Cook, R., & Johannsen, L. (2010). *Behind human error* (2nd ed.). CRC Press.

Zijlstra, F. R. H., Waller, M. J., & Phillips, S. I. (2012). Setting the tone: Early interaction patterns in swift-starting teams as a predictor of effectiveness. *European Journal of Work and Organizational Psychology*, *21*(5), 749–777. https://doi.org/10.1080/1359432x.2012.690399

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APPENDIX A

TABLE A1 Software and visualizations for each analysis technique

Analysis technique	Software and R packages	Availability
Lag sequential analysis	GSEQ (specialized software)	Free at: https://www.mangold-international.com/en/products/software/gseq
T-pattern analysis	THEME (specialized software)	Free educational software, or Paid licence of full access to features www.patternvision.com
Relational event modeling	Relevent informR (R packages)	Free at: http://CRAN.R-project.org/package=relevent http://CRAN.R-project.org/package=informR
Recurrence analysis	nonlinearTseries (R package)	Free at: https://github.com/constantino-garcia/nonlinearTseries/issues
Phase space analysis	GridWare (specialized software)	Paid licence http://statespacegrids.org/
Entropy	nonlinearTseries (R package)	Free at: https://github.com/constantino-garcia/nonlinearTseries/issues
Hurst Exponent	liftLRD (R package)	Free at: https://CRAN.R-project.org/package=liftLRD