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Physiological synchronization and entropy as measures of team cognitive load

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Abstract

The operating room (OR) is a high-risk and complex environment, where multiple specialized professionals work as a team to effectively care for patients in need of surgical interventions. Surgical tasks impose high cognitive demands on OR staff and cognitive overload may have deleterious effects on team performance and patient safety. The aim of the present study was to investigate the feasibility and describe a novel methodological approach to characterize dynamic changes in team cognitive load by measuring synchronization and entropy of heart rate variability parameters during real-life cardiac surgery. Cognitive load was measured by capturing interbeat intervals (IBI) from three team members (surgeon, anesthesiologist and perfusionist) using an un-obtrusive wearable heart rate sensor and transmitted in real-time to a smartphone application. Clinical data and operating room audio/video recordings were also collected to provide behavioral and contextual information. We developed symbolic representations of the transient cognitive state of individual team members (Individual Cognitive State – ICS), and overall team (Team Cognitive State – TCS) by comparing IBI data from each team member with themselves and with others. The distribution of TCS symbols during surgery enabled us to display and analyze temporal states and dynamic changes of team cognitive load. Shannon's entropy was calculated to estimate the changing levels of team organization and to detect fluctuations resulting from a variety of cognitive demands and/or specific situations (e.g. medical error, emergency, flow disruptions). An illustrative example from a real cardiac surgery team shows how cognitive load patterns shifted rapidly after an actual near-miss medication event, leading the team to a more organized and synchronized state. The methodological approach described in this study provides a measurement technique for the assessment of team physiological synchronization, which can be applied to many

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other team-based environments. Future research should gather additional validity evidence to support the proposed methods for team cognitive load measurement.

Keywords

Cognitive load; Teamwork; Surgery; Heart rate variability; Physiological synchronization

1. Introduction

The operating room (OR) is a high-risk and complex socio-technical system in which specialized professionals work as a team, interacting with each other and the patient, using a variety of equipment, technological devices and interfaces [1]. Contributing to the complexity of the OR, patients needing surgery present a wide heterogeneity of medical conditions and severity of illness, making uncertainty and ambiguity part of everyday practice for surgical teams [2]. Intraoperatively, team members must concurrently process a large amount of information (e.g. visual, auditory and tactile) from a wide variety of sources (e.g. patient, monitors, equipment, alarms, other team members). These complexities, alongside the need for coordinated interpersonal interactions, critical communications and high-stake decisions impose extremely high cognitive demands for the OR team [3]. Despite a considerable improvement in surgical safety and patient outcomes in the past two decades, the incidence of errors among surgical patients continues to be elevated, especially in high-risk specialties, with some studies reporting an adverse event rate of 12% among cardiac surgery patients during hospitalization [4]. Among the many factors that contribute to errors in surgery, there is a solid body of evidence showing that preventable errors are often not related to medical knowledge or technical skills, but represent suboptimal performance in non-technical skills, such as situational awareness, decision making, leadership, communication and teamwork [5]. In fact, breakdowns in teamwork, such as communication problems, workflow disruptions, unclear roles and responsibilities and uncoordinated task distribution can impose substantial cognitive demand to surgical teams and are associated with poor patient outcomes [6,7].

In surgery, it is already known that the cognitive load of each key team member (surgeon, anesthesiologist, perfusionist) is highly variable over the course of the procedure, and a high demanding step for a surgeon may impose low cognitive load for the anesthesiologist or nurse, for example [8]. For this reason, assessing the cognitive load of each individual team member is critical, and a wide variety of measurement tools have been applied for this purpose [3]. However, assessing the cognitive load of only individual team members is not sufficient to understand the complex and dynamic relationships that emerge from surgical team activities. Some authors have attempted to define the cognitive load construct at a team level. *Bowers et al.*, for example, describe team workload as *"the relationship between the finite performance capacities of a team and the demands placed on the team by its performance environment."* Nonetheless, in a recent review of the literature seeking to conceptualize and revise measurement of team workload in various fields, *Funke et al.* concluded that *"conception and measurement of team workload have not significantly matured alongside developments in individual workload"* [9]. The authors also highlight that a validated theoretical framework for the construct team cognitive load, which includes a conceptualization of its relation to individual cognitive load, has not yet been articulated. This represents a gap in our current knowledge and requires methodological innovation to understand how individual cognitive load should be composed into a team-level measure.

Regardless of how competent and expert a person may be, they are still subject to the common cognitive limitations that characterize the human brain. In our daily activities, our sensory memory system receives and processes a vast amount of visual and auditory information. Modulated by attention, incoming information is allocated into working memory (WM), which organizes it to be efficiently stored in long-term memory and retrieved when necessary. Although our long-term memory has theoretically unlimited capacity, our WM is able to process only a limited amount of information simultaneously [10,11]. 'Cognitive load' is the most contemporary scientific term that encapsulates a wide variety of terms used to describe the phenomenon of WM utilization (related terms used in the past include: cognitive workload, mental strain and mental effort) [11]. WM limitations largely depend on the novelty of the obtained information, since novel data received from sensory memory impose a higher load and last for a shorter time in the WM compared to information retrieved from long-term memory [12]. For this reason, expertise level (e.g. novice vs. expert) and information source (e.g. planned vs. unexpected) play a critical role on how our WM handles concurrent information and its subsequent impact on human performance [11,13]. Frequently, cognitive load is described using a resource model in which the balance between task demand and cognitive resources determines the workload imposed on an individual [14]. In fact, many assessment tools represent cognitive load as a multifaceted construct that encapsulates several components, such as mental demand, physical demand, temporal demand, performance, effort and frustration [15]. Task complexity is another component that plays an important role on the level of cognitive load posed by certain tasks.

Although many previous studies have investigated the relationship between task complexity and cognitive load at the individual level, scarce literature exists on the impact of task complexity on team cognitive load [9,16,17]. As highlighted by Funke et al. [9] and suggested by the well-established field of distributed cognition, part of the challenge of exploring the relationship between task complexity and team cognitive load is due to the fact that team cognitive load is a function not only of the interactions between individual team members, but also of team member's relationship to the work environment, tools and technologies that the team is embedded in [18]. Furthermore, the literature is also scarce on the development of objective measures of team cognitive load, especially with respect to physiological surrogates. Among the many proposed physiological metrics, a recent meta-analysis suggests that heart rate variability (HRV) measures show sensitivity to task load, conditions of event rate, and task duration [19]. However, most of the previous studies using HRV measured cognitive load at the individual level and few studies attempted to develop aggregation models toward a team cognitive load construct.

Our approach to assess team cognitive load is based on the concept of *neurophysiologic synchronies* [20], also referred to as *physio-behavioral synchronicity* [21] or *social-psychophysiological compliance* [22]. These different terminologies encompasses an unique concept that can be defined as "*the coordinated expression of different levels of neurophysiologic indicators by individuals of a team as they engage in collaborative activities"* [20]. Recent findings suggest that synchronicity of physiological signals (e.g. brain activity) among team members may index the degree of team coordination and cohesion, and the concept of neurodynamic organization has been used to describe the state that arises when teams perform coordinated tasks [23]. It has also been suggested that fluctuations in synchronicity may provide a useful indicator of changes in team cognitive load. There are few studies investigating physiological synchronization in teams, and most of these studies have used electroencephalography and electrocardiography signals of operators in laboratory settings during non-medical tasks [21,23,24] Previous research involving submarine and healthcare teams have shown that neurophysiologic synchronization (electroencephalography) fluctuates with the task demands with increased synchronization occurring when the team needed to resolve uncertainty (e.g. make a decision about whether the patient needs to be intubated or not) [23].

To date, few studies have attempted to investigate the cognitive load imposed by surgical tasks at a team level using objective metrics. Studying physiological synchronization is the first step towards developing measures of cognitive synchronization. The objective of this study was to establish the feasibility of using HRV data for physiological synchronization analysis and the potential for an objective measure of team cognition. We describe a novel methodological approach to measuring synchronization and entropy of heart rate variability parameters among team members during real-life cardiac surgeries. We used interbeat intervals (IBI) averaged to a 2-s epoch, allowing us to detect ultra-short-term fluctuations of physiological synchronization states.

2. Methods

2.1. Study design and setting

In this pilot study, we investigated a cardiac surgical team during an elective procedure in the OR of a tertiary referral hospital (Veterans Affairs Boston Healthcare System - a Harvard Medical School affiliated teaching hospital). The procedure was a coronary-artery bypass grafting surgery (CABG), which is indicated to improve coronary circulation in patients with obstructive coronary artery disease and evidence of ischemia. This is a commonly performed complex type of open-heart surgery that requires a highly specialized team of 8–12 individuals and regularly involves the use of a heart-lung machine (cardiopulmonary bypass) and cardioplegic arrest.

2.2. Participants

The cardiovascular OR team is composed by four sub-teams: the cardiac surgical team with an attending surgeon, one or more residents/ fellows and a surgical physician assistant; the anesthesiology team with the attending anesthesiologist, one or more residents/fellows and a nurse anesthetist; the perfusion team with a lead and an assistant perfusionist; and the nursing team including a sterile scrubbed nurse or technician and a nurse circulator. Audio and video data were collected from the entire team and physiological data was captured from the principal surgeon, anesthesiologist and perfusionist. Regulatory approvals for this research were obtained by the local Institutional Review Board (IRB) of record (IRB#3047) following review by the Privacy Office, Information Security Office, Subcommittee on Human Subjects Protection and the Research and Development Committee. Both patient and OR staff completed a written informed consent.

2.3. Physiological data

Participants wore a heart rate sensor (Polar H7 chest strap) and were simultaneously monitored during the entire procedure. The heart rate sensor captures the intervals between successive heartbeats (interbeat intervals – IBI) in milliseconds and transmits this information via Bluetooth connection to a smartphone app (Elite HRV). After the surgery was completed, raw data (IBI) from each team member was exported in .csv format.

2.4. Contextual and behavioral data

The surgery was audio and video recorded using three lapel microphones (surgeon, anesthesiologist and perfusionist) and two GoPro cameras (narrow and wide field of view). Using this data, a physician with expertise in human factors annotated relevant activities, behaviors, situations and events occurring during the procedure. Clinical data from patient electronic health record (EHR) were also collected for each case.

2.5. Measuring physiological synchronization

To allow comparisons between the three team members, and since the heart does not beat in a fixed rate, each series of recorded IBI was averaged within discrete and consecutive 2-s epochs to generate time-series of equal sampling units. Subsequently, the average IBI of each team member was aligned to the actual surgery time, using a 2-s timestamp (Fig. 1). We used a 2-s epoch because the use of shorter periods, for example 1 s, could generate null data if the IBI was greater than 1000 ms. This situation would happen, for example, every time participants presented a heart rate lower than 60 beats per minute, which is not rare.

To represent the cognitive load based on heart rate variability (HRV) data, we created a symbolic representation of the momentary IBI value for each team member (individual cognitive state - ICS). Subsequently, we determined a collection of ICS that together described the team cognitive state (TCS). The creation of symbols to represent the ICS and the determination of an overall measure of team cognition were based on previous research carried out by *Stevens et al.* on brain electrical activity to investigate neurodynamic organizations [24,25]. We adapted this approach for integration of HRV data. A detailed description of this approach follows below:

2.5.1. Individual cognitive state (ICS)—IBI data collected during the entire surgical procedure was used to calculate terciles (lower, middle and upper) for each team member. At each moment of surgery (2-s epoch), the individuals could be in one of three distinct cognitive states (low, medium or high cognitive load), based on the comparison between the IBI at a particular time point and their own terciles. For visualization purposes, each ICS was combined into a three-element vector. Since a high cognitive load is associated with predominance of sympathetic activity over the parasympathetic tone, the higher the cognitive load, the smaller the IBI [19,26]. Fig. 2 illustrates the ICS of three surgical team members. In this specific moment, the surgeon presented medium, the anesthesiologist low and the perfusionist high cognitive load.

2.5.2. Team cognitive state (TCS)—

The combination of three cognitive load states (low, medium or high) and three team members (surgeon, anesthesiologist and perfusionist), generates 27 possible unique TCS symbols (Fig. 3). This schematic representation can be interpreted as follows: ***TCS 14*** represents a state in which the three team members are synchronized at a medium cognitive load. ***From TCS 13*** **to** ***TCS 1*** there is a trend towards high physiological synchronization and low team cognitive load (high IBI); ***from TCS 15 to TCS 27*** there is a trend toward high physiological synchronization and high team cognitive load (low IBI).

2.5.3. HRV stream—

The vectors (TCS) combining three team member's ICS, and representing the team cognitive load are plotted in a graph that shows the distribution of symbols during the course of surgery for each 2-s epoch. The analysis of distribution patterns enables us to display the temporal information of the team cognitive load (*HRV Stream*), as shown in Fig. 4. Due to the long period displayed in Fig. 4 (140 min – 4200 epochs) there is the false appearance that different symbols overlap at specific time points. However, for each 2-s epoch only one symbol can be expressed from 27 possible symbols. Therefore, it is not possible to different TCS symbols occur simultaneously.

2.5.4. Stream entropy—

The distribution of TCS symbols in a HRV stream was quantified by calculating the *Shannon's* entropy (H), using a 120-second sliding window updated each 2 s. *Shannon's* entropy is measured in information bits and estimates the average minimum number of bits needed to encode a string of symbols, based on the frequency that symbols appears in the HRV stream [27]. The theoretical maximum entropy for 27 unique symbols randomly distributed is H = 4.76 bits. Restricted symbol expression represents low entropy, which means there is higher level of organization in the team. Previous research has suggested that entropy decrease (predominance of certain TCS symbols) may be associated with periods of uncertainty/chaos and high cognitive demand in submarine navigation and healthcare teams [23]. The *R* programming language and *R Studio* software (version 1.0.136) were used to calculate entropy for each 120-s window (60 TCS symbols) using the *'entropy'* package [28].

3. Results

As a control, the TCS symbols generated from an actual cardiac surgery team (Fig. 4A) were randomized prior to calculating the TCS entropy distributed over the same time window (140 min) to create a hypothetical team (Fig. 4B). The occurrence of each 27 TCS and the team entropy levels were compared between both groups. The data stream of the actual surgical team shows substantial fluctuation both in the symbol (TCS) expression and the entropy levels over the course of surgery. On the other hand, when the TCS are randomly distributed, the symbols are more uniformly distributed and the *Shannon's* entropy (H) is constantly higher than in the actual team. This comparison is useful to illustrate how the presented method is able to capture certain patterns of team cognitive states, also indicating that the proposed measures are sensitive to short-term changes overtime.

Using this approach, we could detect dynamic changes in the team cognitive load imposed by different situations in a real-life CABG surgery. In Fig. 4A, a substantial drop in the entropy levels, accompanied by a predominance of symbols 20–27, can be seen between the times 11:01 AM and 11:07AM. Based on the triangulation of behavioral analysis data gathered from the video recordings, during this period, the surgeon had just completed the distal anastomosis of the graft to the coronary artery. Then, the surgical team had to perform the adjustment of the cardioplegia delivery after initial dose. To complete this step, a series of tasks must be coordinated between the surgical team members. Routinely, the surgeon asks the perfusionist to administer the cardioplegia solution and to monitor the heart electrical silence, while she/he continues focused on the complex task of performing coronary anastomosis. Concomitantly, the anesthesiologist must be constantly vigilant about the appropriate level of sedation and patient hemodynamics throughout the cardiopulmonary bypass. By video analysis, we could observe a coordinated exchange of information between the team members, using effective closed-loop communication. This dynamics towards a coordinated team-based task was reflected on the TCS distribution and entropy levels.

In addition to this coordinated team-based task, which commonly occurs during cardiac surgery, we were able to detect an unexpected event during the surgical procedure. An error characterized as a “near-miss” event occurred towards the end of the procedure: Wrong administration of a medication. After the event, a period of high uncertainty occurred, since a prompt decision and course of action should have been made by the team to mitigate the error and avoid patient harm. Based on the audio/video analysis of this procedure and post-event interviews with the OR staff conducted by an interviewer blinded to the physiological data, a moment of integration and collaboration between the team members occurred after the event (approximately 10 min) to rapidly solve the problem, and a high cognitive demand was reported by the team members. In Fig. 5, a decrease in team entropy can be observed after the event, and the symbol (TCS) distribution moved towards a predominance of TCS 20–27 (high synchronization and high team cognitive load).

Based on triangulation of physiological synchronization data from the surgical team, patient data reported in the electronic health record and video-based analysis, we could detect that the wrong procedure was performed by an anesthesia resident, working under the supervision of the cardiac attending anesthesiologist. When the medication error occurred, the attending anesthesiologist was managing the overall flow of cases for the entire OR and was distracted by this secondary task, not being able to maintain the situation awareness needed to properly assist the anesthesia trainee during drug administration. In fact, we can observe on Fig. 5, immediately before the incident, that the team entropy was relatively high and the distribution of TCS symbols was more disperse, indicating a lower level of team synchronization. It may reflect the fact that one of the team members (anesthesiologist) was actually involved with an individual task rather than the primary teamwork.

To compare the proposed method with traditional approaches (aggregating individual measures) for team cognitive load assessment, HRV and Entropy streams were plotted in Fig. 6 alongside two traditional measures: IBI sum and average across team members.

4. Discussion

In the present study, we have described a novel methodological approach to measure physiological synchronization and entropy among surgical team members using heart rate variability data during real-life surgery. We have shown the feasibility of capturing individual physiological data and composing it into an unique measure of team physiological synchronization. In addition, we provided examples to illustrate how these metrics can detect moments of uncertainty that demand coordinated decisions and actions, and imposed high cognitive load at a team level. Among several available physiological-based methods, we used HRV analysis which is a widely adopted tool to objectively assess cognitive load [3].

Recent findings, based on the neurovisceral integration theory, have suggested that cognitive functions are regulated by brain systems also involved in the regulation of the cardiovascular autonomic function, specifically the parasympathetic branch (vagal) of the autonomic nervous system (ANS) [29]. Monitoring the influence of the ANS on the heart rate, by measuring the variability of the intervals between successive beats (interbeat intervals), allows us to indirectly assess the cognitive load imposed by task execution [26,30]. Recent systematic review and *meta*-analysis have suggested that HRV is a reliable and sensitive measure of cognitive load in a variety of settings [19], including surgery [3]. Although most research involving HRV has used time-domain and frequency-domain parameters generated by time series analysis (e.g. SDNN, RMSSD and LF/HF ratio), these parameters are generated for each 5-min or 1-min epochs, not allowing capture of low-latency (few seconds) changes in cognitive states. For this reason, we used the IBI averaged to a 2-s epoch, allowing us to detect ultra-short-term fluctuations of team physiological synchronization states. An interactive dashboard was developed and can be accessed in this we-blink: https://public.tableau.com/profile/cognitus#!/vizhome/HRV_Project_2_teste/Dashboard4?publish=yes.

This visualization interface allows the comparison of HRV streams and entropy levels between different surgical stages and phases. In a previous work [31], our group has developed a similar visual analytic dashboard, enabling the triangulation of individual team member’s cognitive load, hierarchical task analysis, video-based behavioral observation analysis and patient data from real-life cardiac surgery. Future studies can integrate these two approaches to report team cognitive load, represented as physiological synchronization, task complexity and other contextual data gathered from behavioral observation analysis.

Surrogate data testing (hypothetical team in Fig. 4B) helped answer whether the time series data streams carry any information over time. If periods of decreased entropy disappear following randomization of the data streams it indicates that there were meaningful structures in the original data stream. The entropy levels plotted in Fig. 4 can also be interpreted under the efficient coding hypothesis proposed by Barlow [32]. According to this theoretical model, through evolution, the human brain evolved to maximize information transmission and minimize energy expense, particularly under uncertainty. From an evolutionary perspective, neural coding efficiency for sensory and motor tasks means a higher chance of survival. Through these inherited mechanisms, the brains of humans respond to uncertainty by optimizing neural coding. For instance, to deal with a high-stake situation or task, team members would need to become more predictable (i.e. less variable) to each other and this higher predictability could be accomplished by increasing neural and, consequently, behavioral organization. In our study, this increased organization is characterized by increased symbols redundancy. Increased redundancy leads to predominant expression of certain TCS symbols, such as TCS 26 and TCS 27, in which the interbeat intervals (IBI) of individual team members are more synchronized. Increased redundancy of information is common in nature as it is one way to ensure effective communication. The drops in entropy levels observed in Fig. 4A reveals moments in which there is a predominance of certain subset of symbols. Interestingly, team members can be synchronized either at a low (Fig. 4A at 10:30am – "green" predominance) or a high (Fig. 4A at 11:02am – "red" predominance) cognitive load level.

The traditional approaches used to measure team cognitive load have been directly adapted from theories of individual cognitive load, often assuming that the demands imposed to a team can be measured by the aggregation of individual cognitive load levels, as for example, summing or averaging the individual measures across the entire team to compose a team level metric [33]. Our findings showed that HRV and entropy streams provide additional information about the team state, allowing the capture of dynamics changes in team cognitive load which cannot be captured by traditional measures, such as IBI sum and average. Based on the triangulation of data captured by surgical audio and video, our findings suggest that the proposed approach is sensitive to high demanding situations imposed at the team level, which could not be detected by aggregation methods (sum and average across individual team members). However, since this is a pilot study from a single case, future studies should further investigate whether other factors, besides cognitive load, are associated with team physiological synchronization.

Another limitation of traditional linear models attempting to explain team cognitive load is the assumption that the cognitive demand is equally distributed among all team members, and in situations imposing high cognitive demand, all team members will have their cognitive load increased [34]. Even in non-medical fields (e.g. aviation, military) in which research on team performance usually precedes medicine, scarce literature exists, and a theoretical framework still lacks articulation. In fact, research encompassing fields, such as *complex systems*, *system dynamics* and *distributed cognition* have suggested that surgery is a highly complex sociotechnical system with critical requirements for communication and coordination. Team cognitive load should be understood as an emergent property of teams performing tasks, and the relationship between individual and team cognitive load is so complex and dynamic, that involves multiplicative and non-linear relationships, instead of addition models [34–37].

By using HRV data instead of EEG signals to assess team physiological synchronization, our approach presents some advantages compared to previous studies [20], including the fact that heart rate sensors are less obtrusive, inexpensive and less susceptible to interference than EEG devices, allowing the monitoring of teams outside the laboratory in more naturalistic environments, such as OR, emergency room and critical care units. Another advantage of using HRV is the fact that, besides synchronization, we can also infer the team cognitive load level. In fact, our findings show moments of synchronization at both low and high team cognitive load levels. Research using EEG could assess the team physiological synchronization, but no information about cognitive load level can be extracted. A potential disadvantage of using HRV parameters, specially IBI, is the fact that this parameter may not have optimal specificity to uniquely measure cognitive load, receiving influence from other situations, such as psychological stress and physical activity [38].

Our proposed method adds to the current knowledge about team cognitive load, by providing an objective measure that can be continuous tracked in near-real-time. Integrated with patient outcome datasets, these metrics can be used to assess team performance during critical phases of patient care, and in the future, these measurements have the potential to be used for real-time corrective feedback, enabling surgical teams to correct their course of action before errors occur. There is an extensive literature demonstrating that teamwork and coordination are crucial for high quality care and patient safety in surgery and other healthcare settings [4,7,39]. Another important aspect is related to how surgical teams respond to uncertainty and high cognitive demands, and how mitigation strategies are implemented following an adverse event (e.g. surgical complication, or error that results in patient harm). The development of objective measures of team cognitive load may be used to further understand team dynamics and to quantify the relationship between specific team cognitive states and patient safety outcomes.

4.1. Limitations and future directions

One limitation of our method is the fact that a continuous variable (IBI in milliseconds) was categorized in 3 categories (terciles). The rationale was to allow comparisons between different team members in a way that the “synchronization” could be detected by assessing if the team members are at the same (or near) tercile. It could be quartiles or quintiles, for example. However, as more categories we distribute the IBI intervals, more possible symbols will be generated. Three categories (terciles) with 3 participants generate 27 unique possible symbols. If we had used quartiles, a total of 81 symbols would be generated and the interpretation of team synchronization would be more challenging and require more computational power. Future studies should also investigate the psychological equivalents (in terms of cognitive load) of these three physiological states (IBI terciles), something that our study design and findings did not allow.

We captured physiological data from multiple team members, but nurses were not included in the present study. Nurses play an important role in the cardiac OR and should be included in future studies that extend these team cognitive metrics to provide a more holistic measurement of cognition in the OR.

Although cognitive load at the individual level is an important concept and have been studies for many decades, team cognitive load is a construct that still is in formation, especially with respect to physiological surrogate metrics. Our study describes a methodological approach to integrate individual physiological measures into a team construct which presents some explanatory advantages compared to traditional aggregating metrics. However, physiological synchronization between team members not necessarily means cognitive synchronization and future research should gather additional validity evidence to support the proposed method for team cognitive load measurement. Future directions adopting the measurement approach proposed in the present manuscript include further elucidation of important research questions: What is the relationship between certain team cognitive load levels and team performance and patient outcomes? What is the threshold above which the team is overloaded, and performance deterioration starts? Can physiological synchronization be used as surrogate for team performance? Are high performance teams more synchronized than poor performance teams when responding to uncertainty? Furthermore, additional investigation is needed to investigate whether fluctuations in physiological synchronization reflect team cognitive load, solely, or other additional factors, such as psychological stress and copying with uncertainty. Perhaps, simulation-based studies may be able to manipulate task demand and complexity at the team level using standardized protocols, allowing the isolation of the cognitive load construct from other factors that may influence the physiological response of teams.

The methodological approach described in this study can be applied to numerous other fields where teamwork and coordination are crucial for task performance, such as aviation, sports and space. Future studies in surgery can investigate the predictive validity of this approach in terms of the ability of team cognitive load metrics to predict patient outcomes and safety events, and the its potential to advance knowledge of applied cognition in the treatment of hospitalized patients. The proposed method to measure cognitive load at a team level could be further extended to incorporate other physiological signals into the synchronization analysis, such as galvanic skin response, pupil dilation and functional near infrared spectroscopy, since these also provide low latency measures. In addition, future studies should investigate the intricate relationship between task complexity and team synchronization, attempting to elucidate the role of complexity on how individuals coordinate tasks and activities, and how this is reflected in terms of physiological synchronization.

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Surgery Time	Surgeon_IBI (ms)	Anesthesia_IBI (ms)	Perfusionist_IBI (ms)
10:00:08 AM	593	616	898
10:00:10 AM	594	616	904
10:00:12 AM	597	593	933
10:00:14 AM	594	575	883
10:00:16 AM	608	559	864
10:00:18 AM	627	566	756
10:00:20 AM	633	558	836
10:00:22 AM	621	579	856

Fig. 1.
Team member's IBI (in milliseconds) for each 2-s epoch.

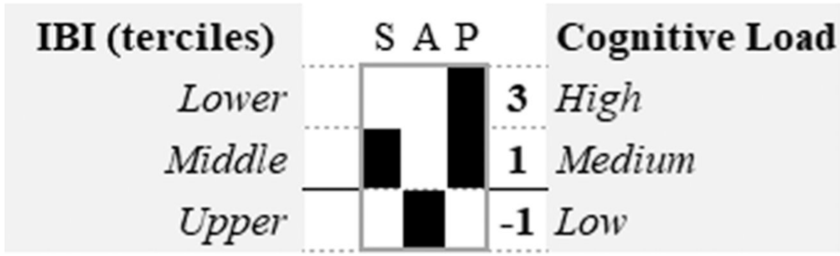

Fig. 2.

Examples of ICS symbols based on interbeat intervals (IBI) from each team member: surgeon (S), anesthesiologist (A) and perfusionist (P).

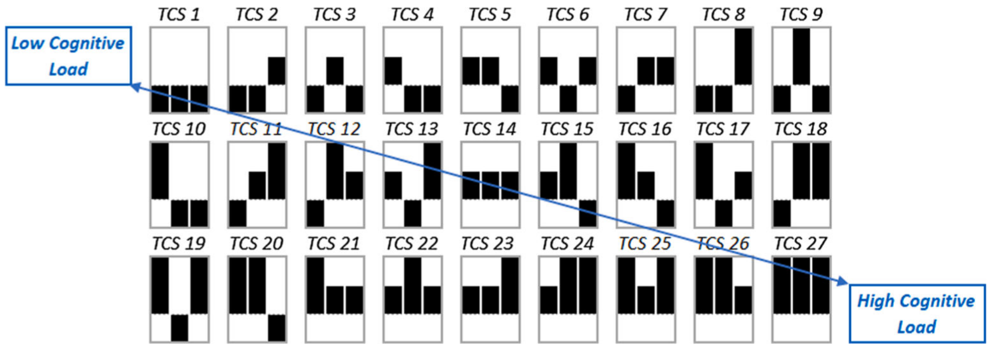

Fig. 3.
Representation of all possible combinations (TCS – team cognitive state) between individual cognitive states (ICS).

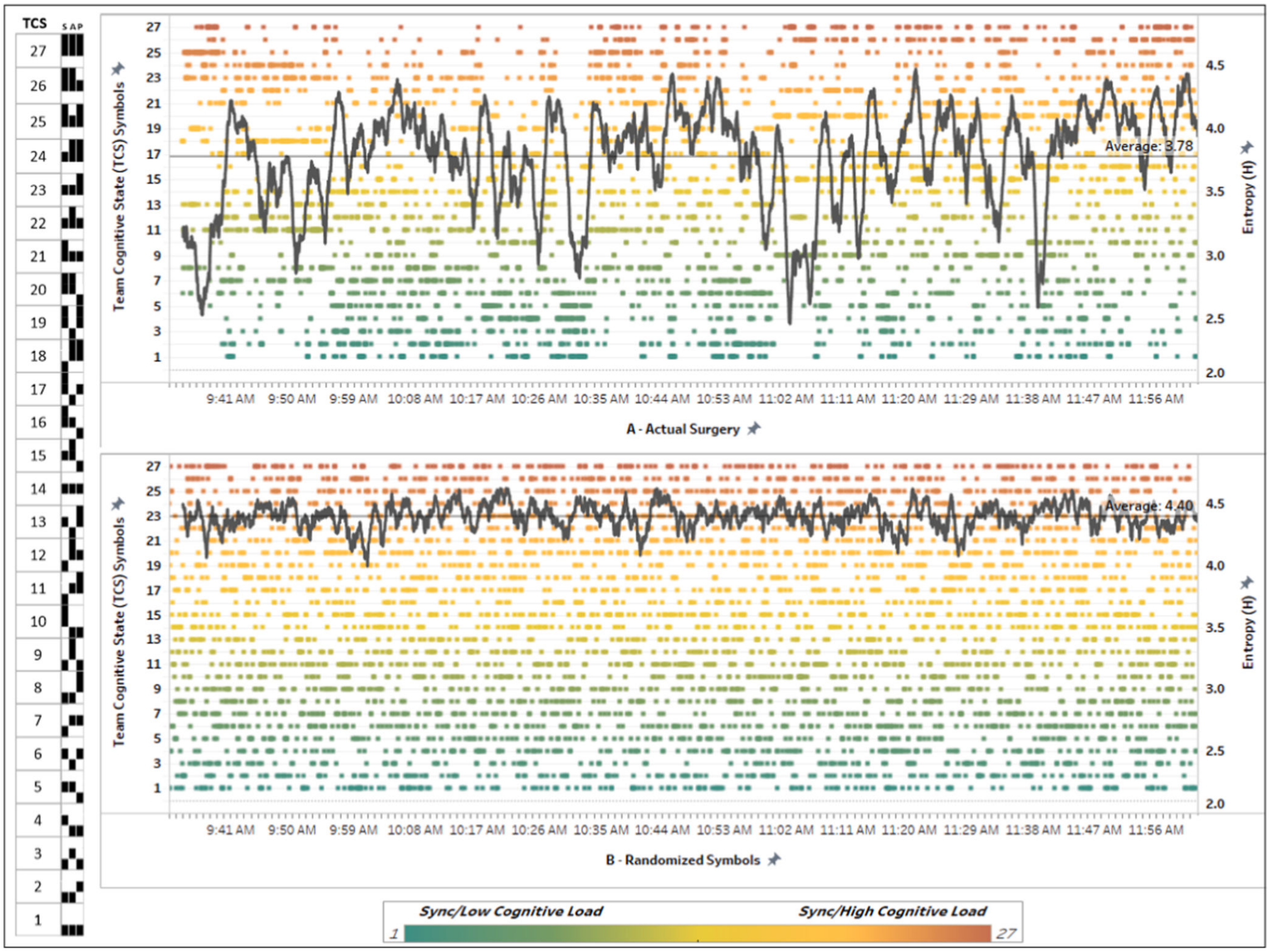

Fig. 4.

Distribution of TCS in an actual surgery (A) and a hypothetical team (B) with randomized symbols. The y axis represents the 27 possible TCS and the x axis shows the surgery time. From TCS 1 to TCS 27 the team cognitive load increases as illustrated in the bottom color-coded tile (green to red gradient). The left bar with TCS shows the combination of individual states (S: surgeon, A: anesthesiologists, P: perfusionist) composing each symbol (refers to Fig. 2 for interpreting individual states). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

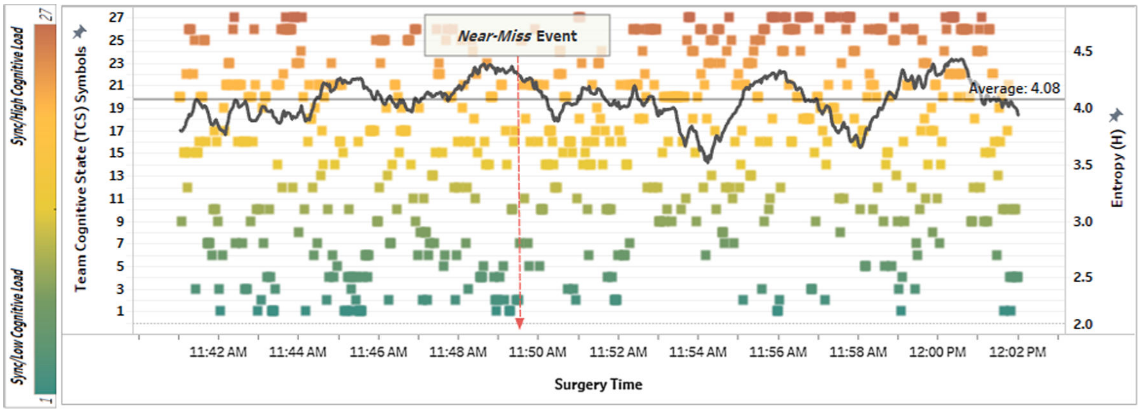

Fig. 5.

Synchronization increase, and entropy decrease after a near-miss event that mobilizes the entire surgical team towards a strategy to avoid patient harm.

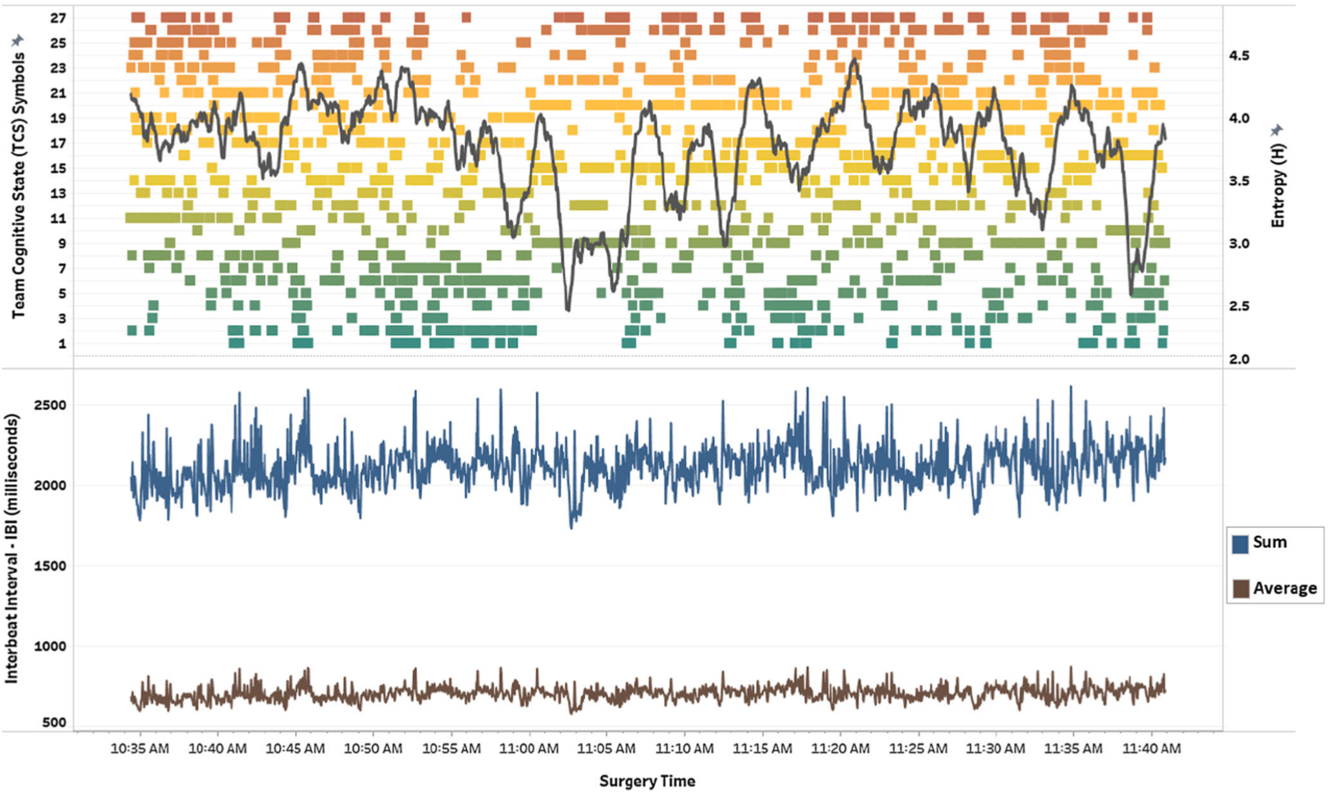

Fig. 6.

Comparison between the proposed approach and traditional measures of team cognitive load.