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Analysis of Dynamic Changes in Cognitive Workload During Cardiac Surgery Perfusionists′ Interactions With the Cardiopulmonary Bypass Pump

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SUPPLEMENTAL MATERIAL
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Abstract

Objective: This novel preliminary study sought to capture dynamic changes in heart rate variability (HRV) as a proxy for cognitive workload among perfusionists while operating the cardiopulmonary bypass (CPB) pump during real-life cardiac surgery.

Background: Estimations of operators' cognitive workload states in naturalistic settings have been derived using noninvasive psychophysiological measures. Effective CPB pump operation by perfusionists is critical in maintaining the patient's homeostasis during open-heart surgery. Investigation into dynamic cognitive workload fluctuations, and their relationship with performance, is lacking in the literature.

Method: HRV and self-reported cognitive workload were collected from three Board-certified cardiac perfusionists ($N = 23$ cases). Five HRV components were analyzed in consecutive nonoverlapping 1-min windows from skin incision through sternal closure. Cases were annotated according to predetermined phases: prebypass, three phases during bypass, and postbypass. Values from all 1min time windows within each phase were averaged.

Results: Cognitive workload was at its highest during the time between initiating bypass and clamping the aorta (preclamp phase during bypass), and decreased over the course of the bypass period.

Conclusion: We identified dynamic, temporal fluctuations in HRV among perfusionists during cardiac surgery corresponding to subjective reports of cognitive workload. Not only does cognitive workload differ for perfusionists during bypass compared with pre- and postbypass phases, but differences in HRV were also detected within the three bypass phases.

Application: These preliminary findings suggest the preclamp phase of CPB pump interaction corresponds to higher cognitive workload, which may point to an area warranting further exploration using passive measurement.

Keywords

physiological measurement; patient safety; physiological psychology; wearable devices; surgical care and procedural technologies

INTRODUCTION

Heart rate variability (HRV) is defined as the measure of fluctuations in consecutive heartbeat intervals (Malik et tal., 1996). As such, HRV provides insight into interactive physiological systems modulating heart rhythm (Rajendra Acharya et al., 2006) and has been used for decades as an unobtrusive measure of physical and psychological states. Conditions associated with HRV levels include stress (Kim et al., 2018), self-regulatory strength, effort, fatigue (McCraty & Shaffer, 2015; Segerstrom & Nes, 2007), changes in task complexity/demands (Luque-Casado et al., 2016), and cognitive load (Hughes et al., 2019; McDuff et al., 2014). The concept of measuring cognitive performance via HRV capture, in particular, is supported largely by the theory behind and empirical evidence generated from the neurovisceral integration model (Thayer et al., 2009, 2012).

Critically, different approaches to analyzing the electrocardiogram (ECG) yield distinct HRV components, which can be categorized as time-domain, frequency-domain, and nonlinear measures depending on the analytic approach employed (Shaffer & Ginsberg, 2017). Since HRV is indicative of the interplay of physiological systems, including the sympathetic and parasympathetic nervous systems (SNS and PNS, respectively), distinct HRV components can be leveraged to infer specific changes in SNS or PNS activity. Specific components that are known to be parasympathetically driven and reliable indicators of a healthier physiological state include time-domain measures such as the root mean square of the successive differences (RMSSD) and percentage of normal-to-normal peaks differing by at least 50 ms (pNN50); and the frequency-domain measure log of the high frequency power band (HF log). Because these measures reflect parasympathetic activity, higher values reflect a more desirable physiological state. This is also true of the average interval duration between consecutive R-peaks (mean RR), which provides the inverse of the average heart rate (HR).

HRV measurement and analysis in monitoring psychophysiological changes of operators working in high-consequence domains are increasingly being investigated (Frazier & Parker, 2019). However, of the 22 articles included in this prior systematic review, only two of those captured physiological responses in naturalistic, real-world settings, and most adopted retrospective analytical approaches. In particular, this illustrates a gap in the literature related to the knowledge about using physiological signals, and specifically of HRV, as measures of operator performance in the wild. With its complex sociotechnical nature, operative surgery is an ideal environment for the application of HRV. HRV is a particularly strong candidate for physiological monitoring given it is continuous, passive, unobtrusive, and noninvasive (Kennedy et al., 2018) and the most frequently utilized measure of physiological fluctuations during actual and simulated surgical procedures (Dias et al., 2018). Within the domain of surgery, cardiac is an especially compelling setting given its multilayered teams including surgeons, cardiac anesthesiologists, operating room (OR) nurses, and perfusionists.

Research into HRV fluctuations among cardiac surgery team members has mainly focused on surgeons, medical students, anesthesiologists, or nurses (Dias et al., 2018) with comparatively less attention to perfusionists (Wadhera et al., 2010), despite their critical role during cardiopulmonary bypass (CPB). The successful execution of CPB necessitates multiple interfaces between the perfusionist and the bypass machine, and human interaction with team members (surgeons, anesthesiologists, nurses); as such, CPB is subjectively determined to be the most cognitively demanding phase of open cardiac surgery for perfusionists (Dias et al., 2019; Wadhera et al., 2010) and the CPB pump can be considered a multifaceted machine requiring constant operator interaction. In particular, the initiation and termination of the bypass phase were shown to induce more stress for perfusionists compared with the stable period in the middle of the bypass phase, according to eyetracking, pupillometry, and the NASA Task Load Index questionnaire (NASA-TLX; Hart & Staveland, 1988) in a recent study (Merkle et al., 2019).

Detailed cardiac surgery process models have been rigorously and iteratively developed with subject matter experts by our group (Avrunin et al., 2018) and utilized to identify key tasks and duties of the perfusionist during each phase of surgery; these include pre- and postbypass phases in addition to CPB itself. During the prebypass phase, perfusionists primarily set up CPB pump lines, establish baseline laboratory values, and calculate the appropriate drug dosages for delivery (e.g., heparin).

Once bypass has been initiated, during the particularly short period of time before placing the aortic cross-clamp (preclamp phase during bypass), perfusionists have multiple primary tasks to ensure successful transition to CPB. These include managing the pump temperature, line pressures, and flow and venous drainage; perfusionists also monitor arterial, cerebral, and venous saturations and prime the cardioplegia lines at this time. This necessitates continuously closed-loop communication with surgeons and anesthesiologists.

Once the aorta is cross-clamped (clamp phase during bypass), critical tasks include general management of CPB flow, oxygen delivery to the tissues, cardioplegia delivery, and monitoring of pressure, temperature, and hematocrit levels. This “clamp phase,” usually extending past an hour, tends to span the longest period of time. After the aortic cross clamp is removed, and before terminating bypass (postclamp phase during bypass), perfusionists continue to monitor venous return and hemodynamic stability; they also prepare to wean the patient off extra-corporeal support. Upon terminating bypass (postbypass), tasks that follow include calculating and communicating protamine dosage for heparin reversal and managing the system used to salvage cardiotomy blood from surgery.

The present study used a preliminary approach to investigate the dynamic fluctuations in HRV among perfusionists before, during, and after the bypass phase of elective, common cardiac surgery procedures. Given the high potential for cognitive overload during the bypass phase of open cardiac surgery while perfusionists toggle between human-machine interaction and team-based communication, this is a critical task for perfusionists and the patients under their care. The role of perfusion is commonly underappreciated, and the scarcity of empirical literature reporting perfusionists’ cognitive workload changes during cardiac surgery illustrates a critical knowledge gap. Beyond the scope of surgery, there is also a notable gap in the collection of physiological signals representative of changing cognitive workload states in naturalistic settings and a lack of validation of those signals against self-reported perceptions.

The aims of this exploratory study were to (a) describe dynamic changes in cognitive workload among perfusionists during cardiac surgery; (b) demonstrate the utility and sensitivity of HRV, as a proxy for cognitive workload, in capturing dynamic fluctuations over time in a naturalistic setting; and (c) fill an existing knowledge gap by illustrating both subjective and objective estimates of cognitive workload. We hypothesize that the bypass phase of cardiac surgery will elicit higher self-perceived reports of cognitive workload compared with pre- and postbypass phases, which would urge further investigation into HRV changes during the bypass phase in particular. We also hypothesize that earlier phases of CPB may reveal HRV indices representative of higher cognitive workload compared with later phases of CPB, given the greater degree of overall demands earlier during the bypass period. With the neurovisceral integration model in mind, we believe that dynamic fluctuations, if detected, could be indicative of objective and temporal changes in perfusionists' high-level cognitive functioning during perfusionist-CPB pump machine interaction.

METHODS

Participants

This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at VA Boston Healthcare System and Harvard Medical School (IRB#3047). Informed consent was obtained from all participants, which included patients and OR staff involved with the procedure. Data were collected during isolated aortic valve replacement (AVR) or isolated coronary artery bypass graft (CABG) procedures in the cardiac OR of a tertiary teaching hospital between January 2017 and November 2018. Data from 23 cases were collected during the study period. Experience of the three perfusionists involved in the 23 cases can be found in Table 1. Overall, the distribution of participation was relatively equal (nine, eight, and six cases) across the three participants.

Equipment

Data sources included two GoPro HERO4 Black Edition cameras (San Mateo, CA) for video capture of (a) the entire OR and (b) the surgical field; 1 Sony ICD-PX440 audio recorder (Tokyo, Japan) for audio capture of the primary perfusionist; one Polar V800 chest strap with H10 sensors (Kempele, Finland) for HR capture of the primary perfusionist; and three self-report cognitive workload indices to retrospectively measure perceived cognitive workload (a) before going on bypass, (b) while on bypass, and (c) after going off bypass.

Self-reported cognitive workload was assessed using a modification of the Surgery Task Load Index (SURG-TLX; Wilson et al., 2011) introduced by Yu et al. (2016). This modified form includes five dimensions of cognitive workload sensitive to intraoperative demands: mental demand, physical demand, task complexity, distractions, and degree of difficulty. Using five visual analog scales ranging from 0 to 100, respondents subjectively assess their perceived cognitive load across each dimension. Higher ratings on these dimensions indicate higher levels of perceived demands, with the highest possible perceived cognitive workload corresponding to a rating of 100.

Study Setup and Environmental Conditions of the Operating Room

A bird's-eye view of the typical OR configuration across the cases analyzed can be found in Figure 1. This figure illustrates where each of the cameras were located, locations of personnel, and an indication of the number of people in the OR on average. Though the cameras were not concealed during data collection, they were small enough to go largely unnoticed by personnel, minimizing the potential to induce the Hawthorne effect.

In general, the number of individuals present in the OR during AVR and CABG procedures tends to range between 9 and 15 providers. The minimum requirement of personnel at a given time (nine) includes teams of surgeons (attending and trainee), anesthesiologists (attending and trainee), perfusionists (primary and secondary), nurses (circulating and scrub tech), and a physician assistant. The highest number of staff in the OR across all 23 cases analyzed was 15, which included additional team members (i.e., a second attending surgeon), medical students, vendors, and/or observers and researchers.

Ambient lighting and OR room temperature tended to be stable across cases, with minimal variation overall (room temperature range: 65–69°F). Background noise varied moderately, but based on preliminary inspection of auditory files, the pre- and postbypass phases were consistently louder than the bypass phase, in all 23 cases. During times requiring a high degree of communication (i.e., separating from bypass), noise in the OR was highest, reaching up to 0.030 RMS on average. This can be compared with analogous periods of time selected from the middle of the corresponding bypass phases (average = 0.022 RMS). Analyses of these data were not incorporated in the original study design, providing contextual but not necessarily robust post hoc analysis.

Finally, the possibility that organizational pressures could influence the OR environment was considered. All 23 cases included in analysis were completed while at least one additional case was underway in another OR at our hospital (total ORs = 6). On average, 3.7 of the 5 remaining ORs were being used concurrently during the analyzed cases. Common concurrent surgeries include those conducted by neurosurgery, urology, vascular surgery, and obstetrics and gynecology departments.

Given the focus on cognitive workload in the operative setting, it is critical to consider the design and functionality of the CPB pump that perfusionists interact with. The design of the Sorin S5 CPB pump machine model in the present study was manufactured by Stöckert (Munich, Germany; seen in Figure 2). The complexity of the design is illustrated by the number of components competing for the perfusionist’s attention, with a compact configuration of 13 displays, all displaying critical information regarding patient parameters. In reference to Figure 1, it is also worth noting that in addition to the multiple displays competing for attention, perfusionists are also tasked with communication hindrances when the attending surgeon and trainee switch positions. In this configuration, the attending surgeon and perfusionist rely on verbal communication alone, without the opportunity to integrate nonverbal cues.

Procedure

Data collection began prior to the patient’s arrival into the OR to ensure minimal interference with sterile prepping procedures, and ended at the patient’s departure from the OR. Following each case, all audio, video, and physiological recordings were manually time synced and integrated by one researcher (LKM). Data were analyzed from the time the patient was transferred onto the operating table until the end of sternal closure. Phases within the procedure were annotated as (a) prebypass (skin incision—initiating bypass), (b) preclamp (initiating bypass—clamping the aorta), (c) clamp time (clamping the aorta—unclamping the aorta), (d) postclamp (unclamping the aorta—terminating bypass), and (e) postbypass (terminating bypass—sternal closure). Identification and annotation of surgical phases was done manually by one coder (LKM).

Within the HRV data collected, we were specifically interested in vagally mediated indicators of cognitive workload, including: RMSSD, HF log, index of the parasympathetic nervous system activity (PNS index), pNN50, and mean RR (Shaffer & Ginsberg, 2017). Although short-term HRV analysis has traditionally been limited to 5-min intervals (Malik et al., 1996), more recent evidence supports the accuracy and reliability of calculating HRV on ultra-short time scales, using time windows as narrow at 10 s (Baek et al., 2015; Munoz et al., 2015; Nussinovitch et al., 2011; Salahuddin et al., 2007; Schaaff & Adam, 2013; Shaffer et al., 2016; Thong et al., 2003). In an effort to capture dynamic fluctuations occurring on short time scales, our analysis involved calculating the ultra-short-term time window of 1 min.

HRV was analyzed by calculating values for each consecutive, nonoverlapping 1-min time window within each surgical phase using Kubios HRV software (Tarvainen et al., 2014), and averaging all 1-min windows within a phase to result in one value for each HRV component per phase. This approach was originally proposed by the Task Force of The European Society of Cardiology and The North American Society of Pacing and Electrophysiology to minimize error arising from data segmentation into very short time windows. Thus, the average of all inclusive 1-min calculations within a given phase represent the HRV value for the duration of that phase.

Statistical Analysis

Statistical analysis was conducted using SPSS version 26.0 (Armonk, NY). Initial calculations were conducted to evaluate intra-class correlations (ICCs) within perfusionists for all SURG-TLX dimensions and all HRV components. Multilevel modeling (MLM) was additionally utilized to determine the degree of variability in HRV measures accounted for by fixed factors for every level of the model (Level 1: intraoperative phases; Level 2: cases; Level 3: perfusionists).

RESULTS

Specific SURG-TLX dimensions, including mental demands, task complexity, and degree of difficulty, varied similarly according to bypass phase, considering aggregated measures across perfusionists. In each of these dimensions, the bypass phase was perceived to be more demanding than the pre-or postbypass phases of surgery (Figure 3). Table 2 lists means and standard errors of the mean.

Because these data are not independent and yielded high ICCs (mental demand ICC = .844; physical demand ICC = .711; task complexity ICC = .871; distractions ICC = .807; degree of difficulty ICC = .896), we considered the trends across individual perfusionists (Figure 4) to gain more insight into individual patterns of change. In the three dimensions showing the most notable trends in Figure 3 (mental demand, task complexity, and degree of difficulty), we see main effects of the individual, and at the same time consistent trends across bypass phases and individual perfusionists. Perceived physical demands and distractions did not follow a consistent pattern across individual providers. Due to high ICCs and a low sample size, we did not run statistical calculations (Musca et al., 2011) but can appreciate the similar pattern of change nonetheless.

To investigate concordance between subjective (SURG-TLX) and objective (HRV) data, we similarly visualized the prebypass, during bypass, and postbypass phases across the HRV measures analyzed. Two components (RMSSD and PNS index) showed the lowest HRV values observed during bypass, with higher values observed during the pre- and postbypass phases (Figure 5). This corresponds to the self-report data, suggesting that the lower RMSSD and PNS index values observed during bypass may be indicative of higher cognitive workload levels.

Due to the pattern of increased perceived cognitive workload and decreased RMSSD and PNS index values during the bypass phase compared with pre- and postbypass phases, we sought to characterize fluctuations in HRV on a more granular scale. To accomplish this, we further subdivided the bypass phase into three separate phases: preclamp, clamp, and postclamp. Given the variety of tasks involved with different bypass steps, calculating the average over the entire bypass period has a high potential to dilute important fluctuations over time.

Analysis of each HRV component included (RMSSD, HF log, PNS index, pNN50, and mean RR) revealed the same pattern across the three bypass phases. In each case, HRV values were at their lowest during the preclamp phase of bypass (indicative of lower parasympathetic tone), increased in value during the clamp phase of bypass and increased further during the postclamp phase of bypass (Figure 6). Table 3 shows the means and standard errors of the means for each component.

Due to high ICCs across perfusionists for each HRV component (RMSSD ICC = .849; HF log ICC = .953; PNS index ICC = .938; pNN50 ICC = .973; mean RR ICC = .982), statistical calculations were deemed inappropriate and therefore not conducted.

MLM was conducted to explore the degree of variation between the level 3 unit of analysis (perfusionists) that could be accounted for by previously collected fixed variables (Peugh, 2010). A three-level MLM was built according to available data sources corresponding to each of the levels, and incorporated the following predictors: Level 1 (intraoperative phases) included phase duration; Level 2 (cases) included patient age, procedure duration, bypass duration, and procedure type; Level 3 (perfusionists) included perfusionist's age and perfusionist's level of postgraduate training (Supplemental Table S1 and S2). Results showed that perfusionist's age was a negative estimate, accounting for significant variation in objective outcome variables (all HRV components: $p < .001$) and perfusionist's experience was a positive estimate, accounting for significant variation in objective outcome variables (all HRV components: $p < .001$). Refer to Supplemental Tables S3a–S3e for detailed information on the estimates of fixed effects for each of the HRV parameters analyzed.

DISCUSSION

We have demonstrated through this preliminary work a general concordance between specific HRV components (RMSSD and PNS index) and subjective perceptions of specific cognitive workload dimensions (mental demands, task complexity, and degree of difficulty) in perfusionists during real-life cardiac surgery, suggesting that cognitive workload changes are mirrored by HRV fluctuations over time. In doing so, our findings support HRV collection as an unobtrusive and continuous reflection of dynamic cognitive workload states in the naturalistic setting of surgery.

The hypothesis-generating work described in this manuscript represents the first study in the literature focusing on human-machine interaction of cardiac perfusionists and objective, continuous indicators of their cognitive workload while operating the CPB pump machine in the context of a cardiac surgery team. Through this novel work, we investigated the patterns of change, according to cognitive workload demonstrated by HRV fluctuations, as perfusionists interacted with the CPB pump machine on a highly sensitive temporal scale. According to RMSSD, HF log, PNS index, pNN50, and mean RR, results showed that the time between initiating bypass and clamping the aorta (preclamp phase during bypass) induced higher cognitive workload (evidenced by lower values) compared with the time on clamp (clamp phase during bypass) and the time between unclamping the aorta and terminating bypass (postclamp phase during bypass). Of course, interpretations must be limited due to the small sample size, individual differences driving results, and a lack of statistical testing.

Nonetheless, it appears that the multiple, and often simultaneous, actions required by the perfusionist during this preclamp phase, with both the CPB pump machine and other members of the surgical team, may be further exacerbated by the short time window in which this typically occurs. In the 23 cases analyzed in this project, the average duration of the preclamp phase was 6 min and 48 s (range 2:37–19:42). In 83% of the cases analyzed, the preclamp phase spanned less than 10 min. The added pressure of temporal demands is unique to this phase, with the next shortest phase averaging at 24 min and 7 s, the postclamp phase, followed by the postbypass phase (57:54), the clamp phase (1:04:12), and the prebypass phase (1:13:20).

Interactions between the surgeon and perfusionist during bypass, and specifically during cardioplegia administration, have been previously defined (Hazlehurst et al., 2007); however comprehensive analyses of the interactions among the perfusionist and CPB pump machine remain largely underexplored. This is a critical area of interest since perfusionists are primarily focused on the bypass pump during the majority of open cardiac surgery cases. Furthermore, while patients are on bypass, they are especially vulnerable to physiological variations with the potential to lead to adverse outcomes (Ottens et al., 2010).

Recent work has elucidated the ways in which cardiac surgery team members' perceptions of cognitive workload vary over the course elective surgery (Dias et al., 2019). By dividing cardiac cases into three distinct phases and conducting a comprehensive cognitive task analysis (CTA), specific phases were identified as more demanding for distinct cardiac surgery team members, including surgeons, anesthesiologists, and perfusionists, which complement previous findings of workload variation across cardiac surgery team members using self-report measures (Wadhera et al., 2010). Beyond the tailored approach to the cardiac surgical setting used in this prior work, CTA represents a highly informative approach to identifying cognitive factors contributing to successful task completion. The application of this approach, in conjunction with HRV analysis, can inform temporal relationships indicative of task performance.

Limited analysis of perfusionists' cognitive workload states during perfusionist-CPB pump machine interaction exists, but more so in the form of subjective reports of workload (Wadhera et al., 2010). Wadhera et al. (2010) evaluated communication breakdowns during critical phases of CPB machine interaction before and after implementation of a protocol-based communication tool intervention. These critical stages of a CPB were identified based on times when effective communication was determined to be critical to ensuring success. The only critical stage identified that presented communication breakdowns both prior to and following their intervention was placement of the cross clamp. Our findings from this study support that the time leading up to cross-clamp placement (preclamp) represents the highest degree of cognitive workload, demonstrated through HRV values.

Patterns of elevated cognitive workload leading up to cross-clamp placement suggested here, coupled with a high potential for communication breakdown (Wadhera et al., 2010), support further investigation into cognitive support for workload management during this time. The need for such investigation in the realm of perfusionist-CPB pump machine interaction is further warranted given that high cognitive workload is a long-documented and a well-defined source of error during human-machine interaction (Card et al., 1983; Kieras et al., 1988; Olson & Olson, 1990).

Monitoring for patient status changes in real time using dynamic interfaces, such as those equipped to the CPB pump machine, can enable more timely behavioral responses by the perfusionist operator (Ottens et al., 2010); this has been demonstrated in the cardiac surgery OR with prior studies (Beck et al., 2015). Although real-time monitoring tasks have the advantage of preventing adverse outcomes during the course of surgery, they also have the potential to produce fatigue or underload states for operators (Embrey et al., 2006). Comparably higher levels of vagally mediated HRV measures observed in this study during the clamp and postclamp phases, reflective of lower cognitive workload states, corroborate this further.

This study has a number of limitations. Ultimately, the most prohibitive limitation is that the participant pool was limited to only three individuals. Despite an otherwise adequate sample size of 23 total cases and the relatively even distribution of perfusionists across cases (nine, eight, and six cases for the three subjects), the nested nature of data along with high ICCs corresponding to individual perfusionists made statistical testing inappropriate. Trends observed may speak more to the idiosyncrasies of the individual perfusionists participating in this study, urging for a larger sample size for future work.

Additionally, this evaluation included only HRV and SURG-TLX as the parameters of interest. Future work should aim to classify behaviors to investigate the correspondence between HRV and other psychophysiological measures, as well as observable patterns such as the taxonomy of nontechnical skills (communication, leadership, decision-making, teamwork; see Yule et al., 2008).

Finally, the types of procedures included in this analysis (namely AVR and CABG) exclude additional complexities that may be observed in more complex procedures (e.g., deep hypothermic circulatory arrest). Thus, these analyses may not be representative of or generalizable to higher complexity cases, which is an area that could benefit from similar investigation in the future.

Beyond the specialty of perfusion and the realm of healthcare altogether, establishing a relationship between task, physiology, perceived cognitive workload, and operator performance in the wild can have broad implications. Robot-assisted surgery, for example, represents a rapidly expanding field within healthcare accompanied by high potential for cognitive overload (Sexton et al., 2018). Outside of healthcare, many high-risk, high-consequence domains have already demonstrated an interest in investigating physiological parameters and their alignment with psychological variables and performance. A critical application upon acquiring knowledge of workload via these disparate sources is the use of biofeedback, a coping intervention employed in many domains (Kennedy et al., 2019), which is underinvestigated in healthcare settings. In all of these cases, the traditional NASA-TLX or modified equivalent can be supportive of findings, but incorporating physiological variables such as HRV simultaneously presents the opportunity for a continuous view of changes on ultra-sensitive timescales.

RECOMMENDATIONS

Data from this preliminary study have demonstrated the diversity in individual physiological responses, despite a shared perception of certain dimensions of cognitive workload during surgery. Despite the small sample size of participants included in these analyses and necessity for future work to expand upon the current work, this particular finding emphasizes that individual differences are critical when developing interventions to address issues such as cognitive overload. Specifically, it is crucial to consider contributing factors such as age and level of experience in order to tailor approaches to specific individuals.

With objective knowledge of individuals' cognitive workload levels over the course of interactions with the CPB pump machine, efforts can be taken to ensure appropriate workload management at critical stages, including the time leading up to placing the cross clamp. While providing additional sensory feedback through visual or auditory modalities may add further to workload levels at the moment, prior and/or post hoc briefing could be established as a training opportunity to increase self-awareness. The greatest value of such training would likely be for less experienced operators, but may also benefit experienced perfusionists who encounter unexpected low-frequency, high-consequence events intraoperatively. Deliberate design and positioning of the OR operators and machines has also shown to contribute to enhanced situational awareness and communication.

CONCLUSIONS

The results of this exploratory study suggest that cognitive workload, according to subjective reporting through the SURG-TLX questionnaire, was notably elevated during the bypass phase of cardiac surgery compared with pre- and postbypass phases. Analysis of various objective components of HRV supports that within the bypass phase, cognitive workload was highest during the time between initiating bypass and clamping the aorta (preclamp phase) compared with other phases of cardiac surgery. Given the complexity associated with this surgical phase, both in terms of technical-based perfusionist-CPB pump machine interaction and communication-based perfusionist-surgeon and perfusionist-anesthesiologist interaction, cognitive overload during this time has a high likelihood of occurrence.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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KEY POINTS

- The exploratory work described in this manuscript represents the first study in the literature focusing on perfusionists and objective, continuous indicators of their cognitive workload while operating the CPB pump in the context of a cardiac surgery team during real surgical procedures.
- Vagally mediated measures of HRV suggest higher cognitive workload during the time between initiating bypass and placing the aortic cross clamp compared with other phases.
- Due to the additional susceptibility to communication breakdown leading up to clamp placement, the preclamp phase during CPB could be a worthwhile target for cognitive support aimed at managing workload levels during perfusionist interaction with the bypass machine.
- Interpretation of these results should be taken with caution, given the small sample size and large degree of ICC among perfusionists.
- HRV is a sensitive measure able to capture temporal fluctuations in cognitive workload during human-machine interaction in a socio-technically complex naturalistic setting.

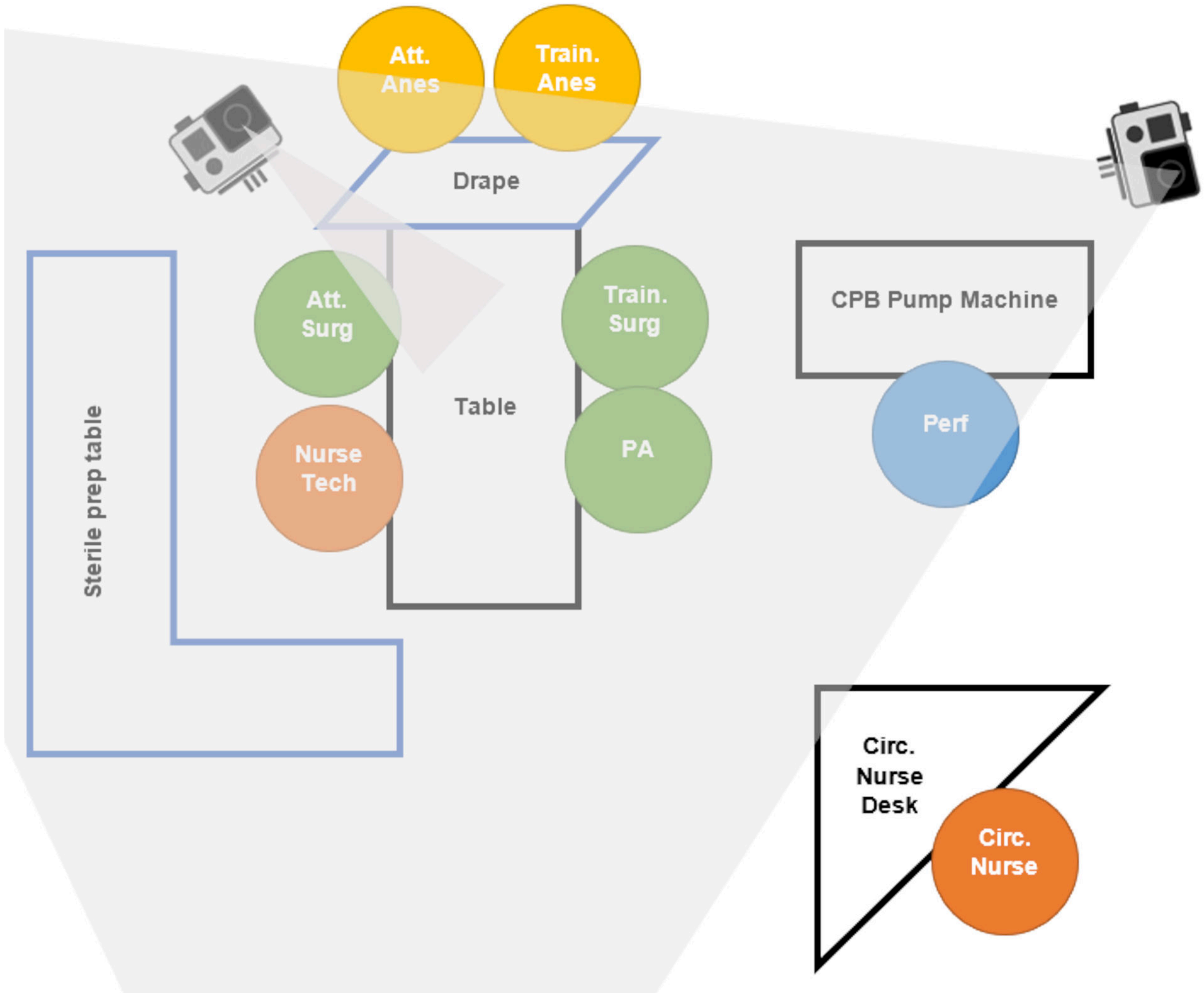

Figure 1.

Typical operating room configuration, including GoPro cameras and their field of view for data collection and key personnel involved. Att. = attending; Train = trainee; Anes = anesthesiologist; Surg = surgeon; Perf = perfusionist; Circ = circulating; CPB = cardipulmonary bypass.

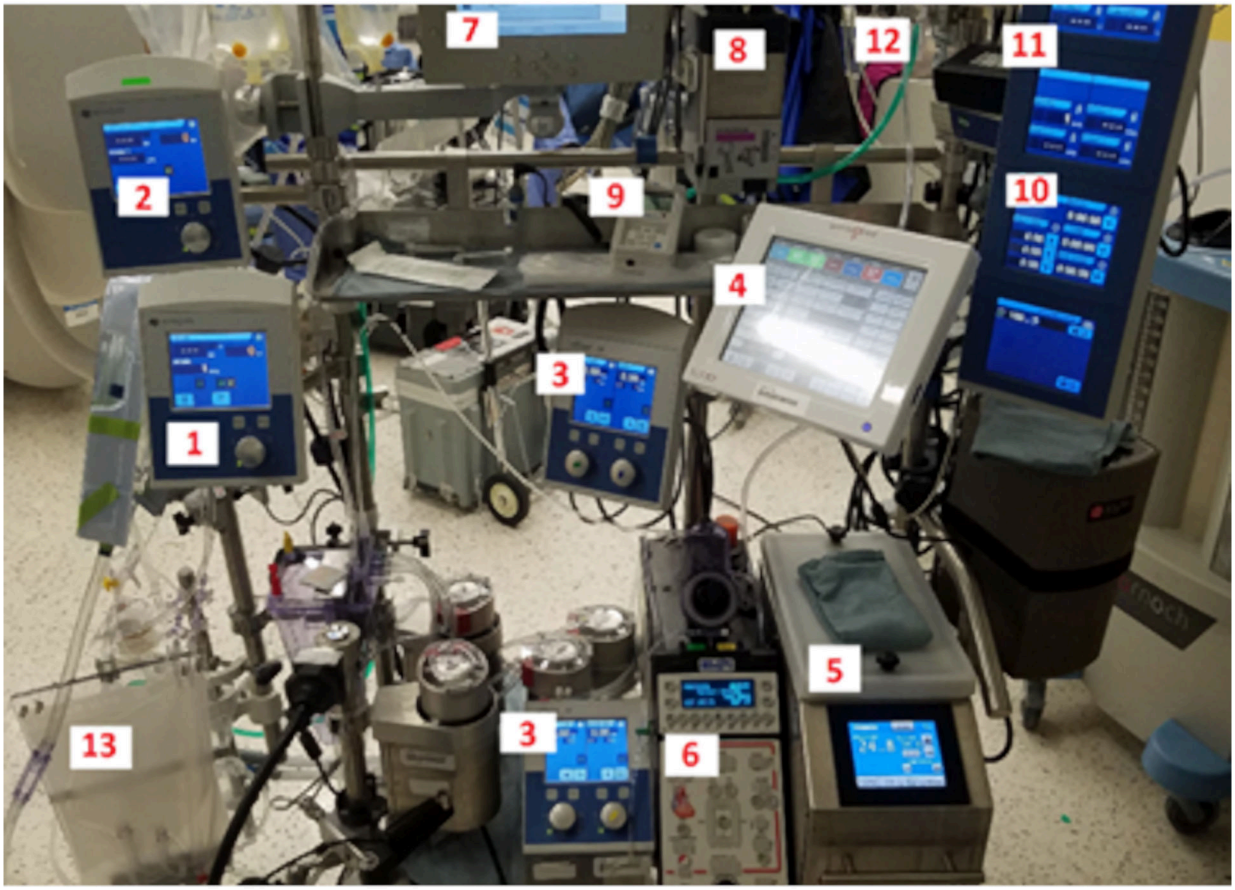

Figure 2.

Stöckert Sorin S5 Heart Lung Machine including the following components: 1) arterial pump module, 2) secondary arterial pump module, 3) pump sucker/vent controls, 4) Viper Data Management System, 5) Cardioquip heater/cooler, 6) MPS Cardioplegia delivery system, 7) CDI 550 blood gas monitor, 8) isoflorane vaporizer, 9) oxygen monitor, 10) pump timers, 11) pump pressure sensors, 12) gas blender, and 13) blood reservoir.

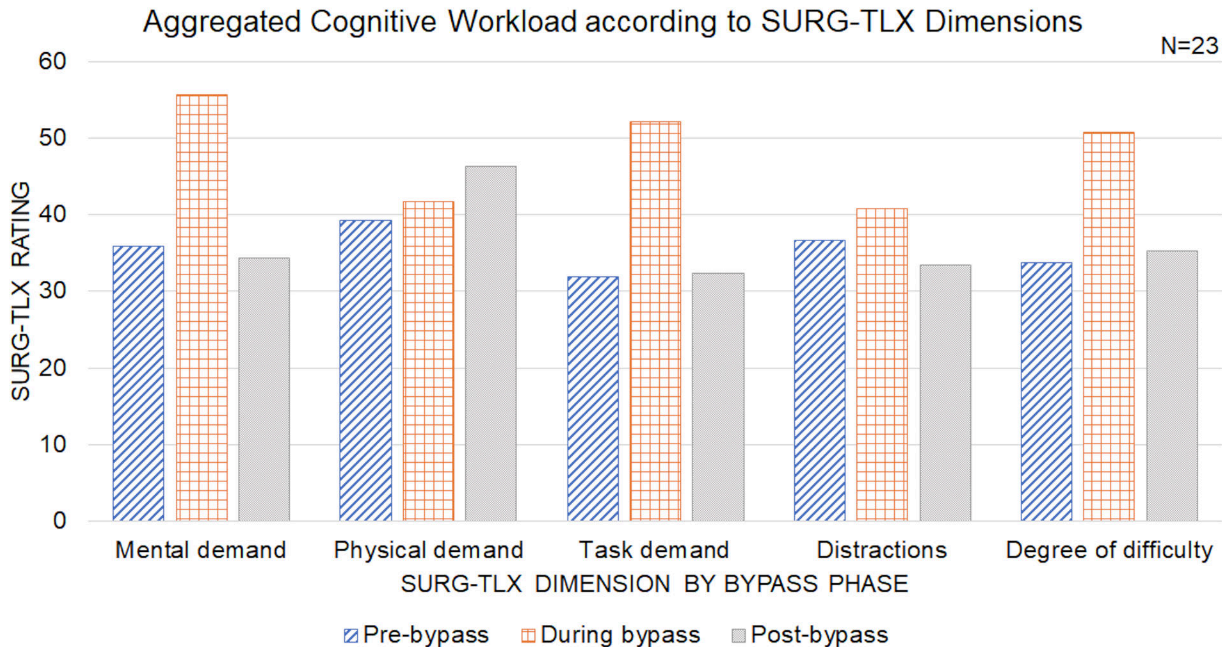

Figure 3.
Self-reported perceptions of cognitive workload dimensions according to the SURG-LX, completed retroactively to indicate cognitive workload levels prior to going on bypass, during bypass, and after bypass. SURG-TLX = Surgery Task Load Index.

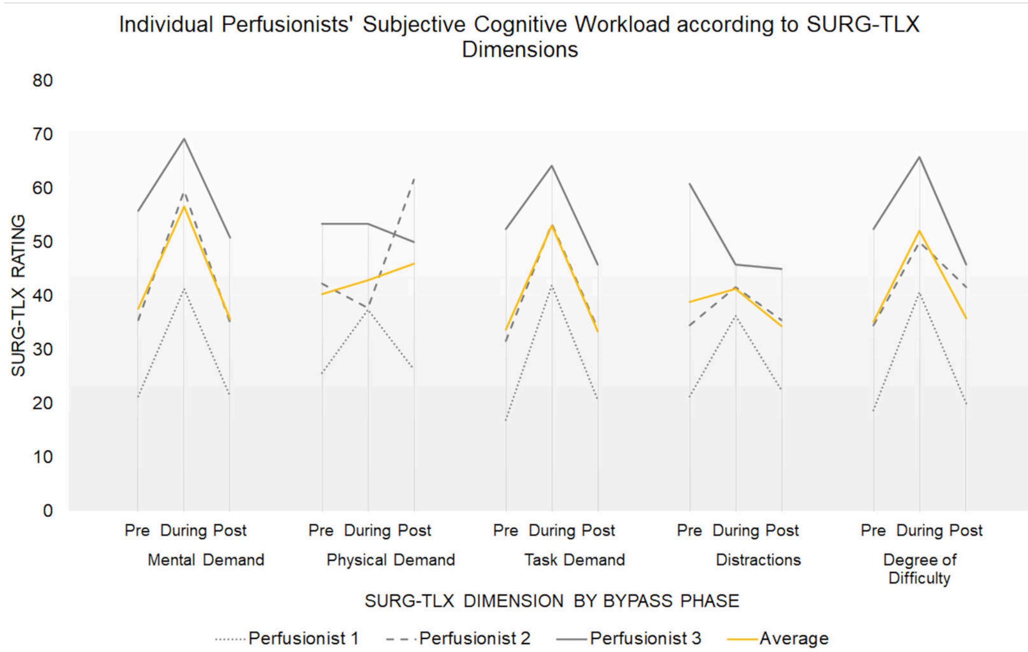

Figure 4.
Self-reported perceptions of cognitive workload dimensions according to the average SURG-TLX ratings across 23 cases, broken down by individual perfusionist. SURG-TLX = Surgery Task Load Index.

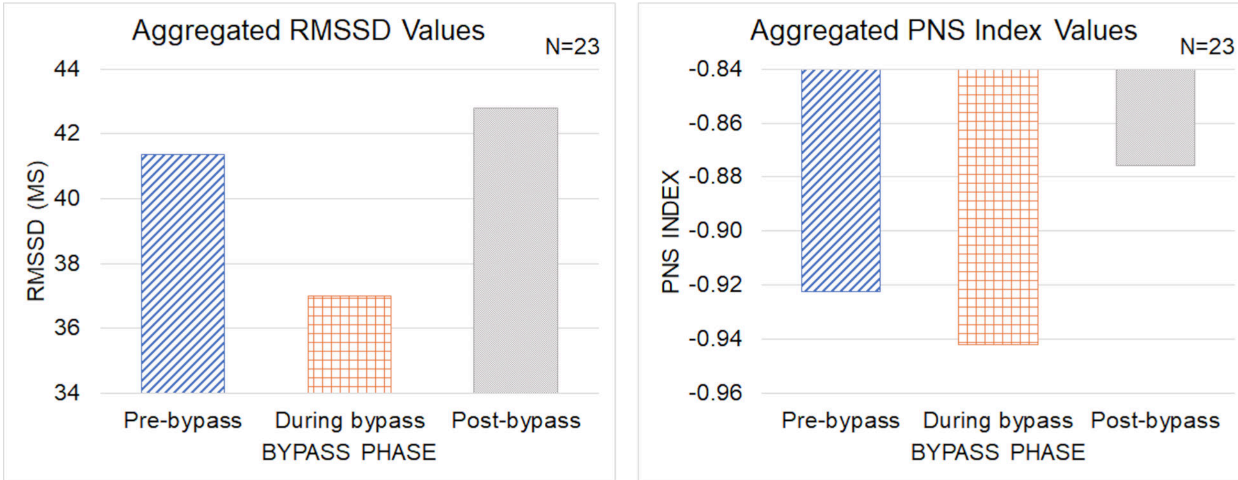

Figure 5.

Aggregated values of RMSSD and PNS index during prebypass, bypass, and postbypass phases, collapsed across all three perfusionists throughout 23 total cases. PNS = parasympathetic nervous system; RMSSD = root mean square of the successive differences.

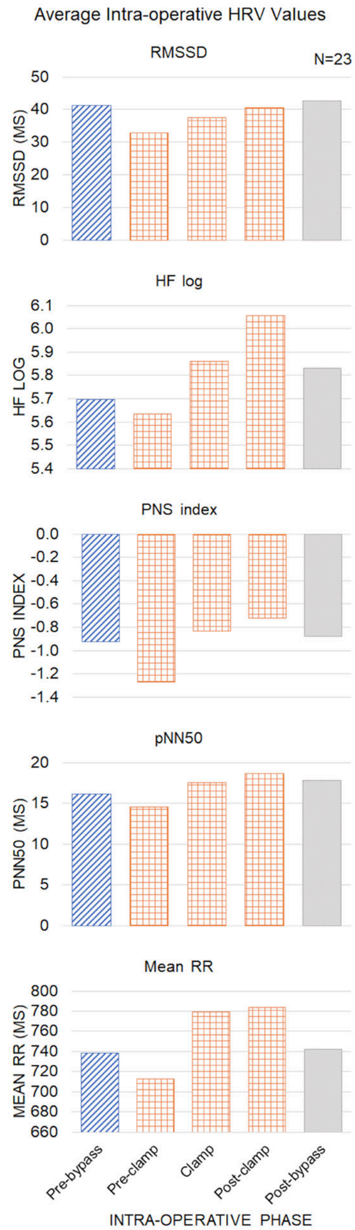

Figure 6.

Average HRV values for RMSSD, HF log, PNS index, pNN50, and Mean RR during prebypass, preclamp, clamp, postclamp, and postbypass phases, collapsed across all three perfusionists during 23 total cases. HF = high frequency power band; HRV = heart rate variability; mean RR = average interval duration between consecutive R-peaks; pNN50 = percentage of normal-to-normal peaks differing by at least 50 ms; PNS = parasympathetic nervous system; RMSSD = root mean square of the successive differences.

TABLE 1:

Participant Characteristics of the Perfusionists Recorded in the 23 Cases Analyzed

Sex: Male (%)	3 (100)
Age: Average (range)	46 (32–60)
Years of Experience (Post-training): Average (range)	19.33 (9–32)
Cardiac Surgeries Performed (Approx.): Average (range)	1933 (700–3500)

TABLE 2:

Descriptive Statistics for SURG-TLX Dimensions Over the Three Bypass Phases

	N	Mean	Standard Error
Mental demands prebypass	23	35.87	4.42
Mental demands during bypass	23	55.65	3.70
Mental demands postbypass	23	34.35	3.70
Physical demands prebypass	23	39.35	4.39
Physical demands during bypass	23	41.74	2.82
Physical demands postbypass	23	46.30	5.08
Task complexity prebypass	23	31.96	3.81
Task complexity during bypass	23	52.17	3.16
Task complexity postbypass	23	32.39	3.14
Distractions prebypass	23	36.74	4.83
Distractions during bypass	23	40.87	2.57
Distractions postbypass	23	33.48	3.15
Degree of difficulty prebypass	23	33.70	4.04
Degree of difficulty during bypass	23	50.87	3.34
Degree of difficulty postbypass	23	35.22	4.35

Note. SURG-TLX = Surgery Task Load Index.

TABLE 3:

Descriptive Statistics for HRV Components Over the Five Intraoperative Phases

	N	Mean	Standard Error
RMSSD prebypass	23	41.35	7.34
RMSSD preclamp	23	32.94	4.13
RMSSD clamp	23	37.54	4.18
RMSSD postclamp	23	40.56	4.24
RMSSD postbypass	23	42.79	6.54
HF log prebypass	23	5.70	0.27
HF log preclamp	23	5.64	0.23
HF log clamp	23	5.86	0.21
HF log postclamp	23	6.06	0.20
HF log postbypass	23	5.83	0.26
PNS index prebypass	23	−0.92	0.27
PNS index preclamp	23	−1.27	0.21
PNS index clamp	23	−0.83	0.22
PNS index postclamp	23	−0.72	0.20
PNS index postbypass	23	−0.88	0.26
pNN50 prebypass	23	16.13	3.29
pNN50 preclamp	23	14.55	3.33
pNN50 clamp	23	17.52	3.35
pNN50 postclamp	23	18.65	3.34
pNN50 postbypass	23	17.82	3.53
Mean RR prebypass	23	738.65	20.56
Mean RR preclamp	23	712.89	19.48
Mean RR clamp	23	779.21	21.85
Mean RR postclamp	23	783.69	20.30
Mean RR postbypass	23	742.50	19.45

Note. HF = high frequency power band; HRV = heart rate variability; mean RR = average interval duration between consecutive R-peaks; pNN50 = percentage of normal-to-normal peaks differing by at least 50 ms; PNS = parasympathetic nervous system; RMSSD = root mean square of the successive differences.