Investigating Cognitive Load in Emergency Control Room Simulations

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ABSTRACT

We propose a novel approach to measure cognitive load in emergency control room operators using their breathing patterns. By using LstSim, a community-driven emergency control room simulator, we aim to recreate the work environment of a dispatcher, induce a cognitive load, and measure the response in the user's breathing. Participants were monitored and recorded through wearable sensors, depth cameras below the screens, and simulation-internal parameters and interactions. The participants' breathing patterns were analyzed to identify changes in breathing amplitude in response to varying levels of cognitive load. The results of our study provide compelling evidence that a simulated control room environment is successful in inducing cognitive load on participants shown in a significant increase in NASA TLX scores as well as a 13% increase in breathing amplitude. Despite the challenges posed by this individual variability, our findings also highlight the potential of using breathing as a real-time, noninvasive measure of cognition in control rooms. This has significant implications for the design and operation of emergency control rooms, potentially leading to the development of more responsive systems that adapt to the operator's cognition load, thereby enhancing performance and effectiveness.

KEYWORDS

datasets, cognitive load, control room, simulation

1 INTRODUCTION

The rapid advancement of monitoring technologies has led to the development of increasingly complex systems that require human interaction. One such system is the emergency control room, a critical component of emergency response services worldwide. These control rooms are often characterized by high-stress environments, where operators must make quick, accurate decisions under significant cognitive load. Understanding and managing this cognitive load is crucial to improving operator performance and, ultimately, the effectiveness of emergency response services.

Cognitive load refers to the total amount of mental effort being used in the working memory [14]. It is a multidimensional construct that includes intrinsic load, extraneous load, and germane load. Intrinsic load is related to the task complexity, extraneous load to the manner in which information is presented to the user, and germane load to the processing, construction, and automation of schemas. A high cognitive load can lead to operator errors, decreased performance, and increased stress, making it a critical factor to consider in the design and operation of emergency control rooms.

Traditionally, cognitive load has been measured as an aspect in user modeling [11] using subjective methods, such as self-report scales, or objective methods, such as performance measures and physiological measures. However, these methods have limitations. Self-report scales rely on the individual's ability to introspect and may not accurately reflect the actual cognitive load. Performance measures can be influenced by factors other than cognitive load, such as skill level and motivation. Physiological measures, such as heart rate and skin conductance, can provide continuous, real-time indicators of cognitive load, but they can also be affected by physical activity and emotional state.

In this study, we propose a novel approach to measure cognitive load in emergency control room operators using their breathing patterns. Breathing is an automatic process regulated by the autonomic nervous system, and changes in breathing patterns have been linked to cognitive and emotional states. Changes in breathing pattern offer the possibility to have a continuous indicator for the cognitive state with a high signal to noise ratio and a non-invasive way of monitoring. By using LstSim, a community-driven Emergency Control Room simulator, we aim to recreate the work environment of an emergency control room dispatcher, induce a cognitive load, and measure the response in the user's breathing.

Our goal is to establish breathing as a reliable modality to measure cognitive load in control rooms. This could potentially lead to the development of more responsive control rooms that adapt to the operator's behavior, thereby reducing cognitive load, improving performance, and enhancing the effectiveness of emergency response services.

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2 RELATED WORK

The concept of using simulations to induce cognitive load and measure its effects has been explored in various contexts [13]. For instance, Brouwers et al. conducted a study using a simulated rail control task to examine the association between cue utilization and performance. They found that participants with a greater level of cue utilization recorded a consistently greater response latency, suggesting a strategy that maintained accuracy but reduced the demands on cognitive resources [1].

In the context of automated driving, Du et al. investigated the relationships between takeover performance and drivers' cognitive load, takeover request lead time, and traffic density in a driving simulation experiment. Their findings highlight the complex interplay between these factors and their impact on performance [5].

In addition to the use of control room simulations, the use of physiological measures, such as breathing, as a modality for cognitive load has been explored. McDuff et al. demonstrated that changes in physiological parameters, including breathing rate, during cognitive stress can be captured remotely, suggesting the potential for non-invasive measurement of cognitive load [12].

A systematic review by Grassmann et al. found that mentally demanding episodes are marked by faster breathing and higher minute ventilation, indicating that changes in breathing patterns can reflect cognitive load [7].

The findings of Grassmann et al. that cognitive load alters the breathing pattern are echoed in the work of other researchers. Brumback et al. demonstrated that changes in physiological parameters, including breathing rate, during cognitive stress can be mitigated using meditation and breathing techniques [2]. Similarly, Jaiswal et al. found that breathing as physiological response is a useful indicator to classify cognitive load [9]. Breathing as a modality for cognitive load has been the focus of several studies, each employing unique methodologies and yielding insightful results. Zhou et al. made significant strides in this area by employing breathing as a modality to record a multimodal dataset for analyzing cognitive load. Their work demonstrates the potential of integrating breathing measurements with other modalities to provide a more comprehensive understanding of cognitive load [15].

Buonviso et al. took a different approach, focusing on the plasticity of breathing during cognitive tasks. Their work highlights the dynamic nature of breathing and its potential to adapt and change in response to cognitive demands, further underscoring its utility as a measure of cognitive load [3].

In a novel application of technology, Cho et al. used thermal imaging to detect breathing patterns and used these for automatic stress analysis using deep learning. This innovative approach not only confirms the link between breathing and cognitive load but also opens up new possibilities for non-invasive and real-time monitoring of cognitive load [4].

Ferreira et al. also recognized the value of breathing as a measure of cognitive load, using it as one of many psycho-physical measures to assess real-time cognitive load. Their work underscores the value of a multi-faceted approach to understanding and measuring cognitive load [6].

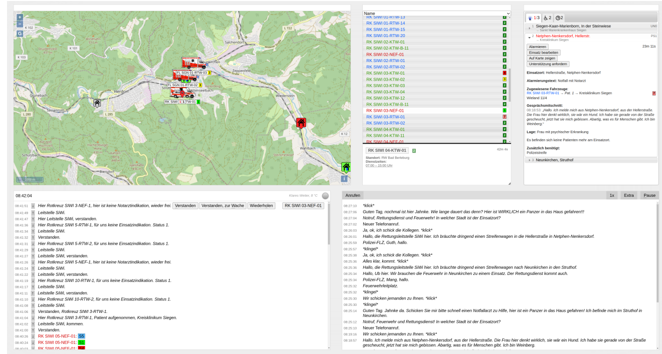

Figure 1: Overview of the interface of the LstSim simulation, a web-based simulator that is maintained by a strong community of control room operators. It contains the major elements of a typical dispatch control room.

These studies collectively illustrate the growing recognition of breathing as a valuable and informative modality for assessing cognitive load. They also highlight the diverse methodologies that can be employed to capture and analyze breathing data, from traditional physiological measurements to more novel techniques such as thermal imaging and deep learning.

Furthermore, Haase et al. found that mindfulness training attenuated the neural response to loaded breathing, suggesting that cognitive strategies could modulate the physiological response [8].

3 LSTSIM: A COMMUNITY-DRIVEN SIMULATOR FOR EMERGENCY CONTROL ROOMS

LstSim is a pioneering tool in the realm of control room simulation, developed with the active participation of the operator community. This web-based game is designed to mimic the real-world tasks and challenges faced by control room operators, providing a realistic and immersive environment for research and training.

The interface of LstSim is modeled closely after the actual work environment of an operator. Central to this interface is a dynamic map that displays the city under the operator's control. Each vehicle under the operator's command is represented on this map, allowing the user to monitor their positions and movements in real-time. This visual representation aids in spatial awareness and decision-making, two critical aspects of control room operations.

Alongside the map is a phone panel, simulating the communication aspect of the operator's role. Incoming calls to this panel represent emergency situations that the operator must manage. These calls, which can range from minor incidents to major disasters, require the operator to quickly assess the situation, dispatch the appropriate resources, and coordinate the response efforts. The unpredictability and urgency of these calls add an element of realism to the simulation, mirroring the high-stakes nature of emergency control room operations.

The integration of these features into a single interface presents the operator with a multifaceted cognitive challenge. They must maintain situational awareness, manage resources efficiently, and make rapid decisions under pressure. This cognitive load, representative of the demands faced by real-world operators, provides a valuable platform for studying the effects of such load on operator well-being and performance.

LstSim's community-driven development approach ensures that the simulation remains grounded in the realities of control room operations. Feedback from the operator community is continually incorporated into the design and refinement of the simulation, ensuring that it accurately reflects the evolving challenges and complexities of the control room environment.

4 SIMULATION ENVIRONMENT: REPLICATING THE CONTROL ROOM EXPERIENCE

In order to capture the essence of the workplace environment of an emergency control room operator, we extended LstSim to a multi-monitor solution. This setup was designed to mimic the physical layout and functionality of a real control room, providing a more authentic simulation experience. The image below shows a typical control room used for emergency operations. Multiple monitors are employed to display various types of information, including maps, resource status, and incoming communications. The operator is seated at a desk, surrounded by these screens, and must constantly monitor and interact with them to manage the ongoing operations.

Our simulation setup, as shown in the following image, replicates this multi-monitor environment on a smaller scale. We arranged multiple monitors on a desk, each displaying a different aspect of the LstSim interface. This setup allows the participant to experience the cognitive load and spatial awareness challenges associated with managing multiple information sources, similar to a real control room operator.

In our simulated environment, each participant plays three sessions of 20 minutes each. The first session serves as a learning and exploration phase, with tutorial hints provided to guide the participant through the various tasks and functionalities of the simulation. This session allows the participant to familiarize themselves with the interface and operations, preparing them for the more challenging sessions to come. The second session mimics a routine operation environment, characterized by a low volume of calls. This session allows the participant to experience the steady-state cognitive load associated with monitoring and managing ongoing operations. The third session, in contrast, mimics emergency operations, where the operator is inundated with calls. This session simulates the heightened cognitive load and stress associated with managing a surge of emergencies, providing valuable insights into how operators handle such situations and the impact on their well-being.

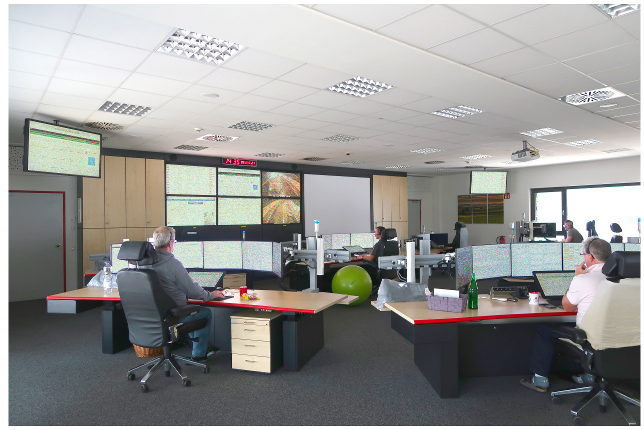

Figure 2: View of the control room of the emergency dispatch center [anonymized for double-blind review], where emergencies are taken on, and following measures are directed by, a team of operators. The system manifests itself for each operator mostly as a desktop-based system with additional screens in the environment.

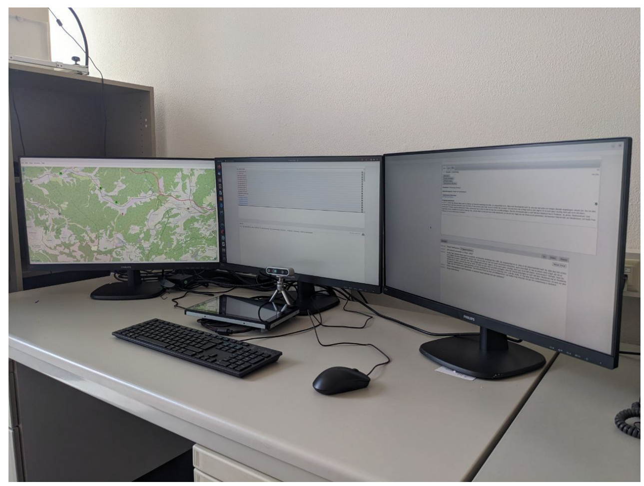

Figure 3: Our LSTSim-based simulation setup, following a similar single user setup across three large desktop screens with a central touch screen. Study volunteers were monitored and recorded through wearable sensors, a depth camera below the screens, and simulation-internal parameters and interactions.

5 STUDY DESIGN AND PARTICIPANTS RECRUITMENT

The participants for this study were recruited from the local population as a convenience sample. A total of 10 individuals initially volunteered and performed all simulated scenarios for the study.

The study was conducted with the approval of the Ethics Council of our local university. All participants provided their informed consent before participating in the study.

Before the commencement of the study, participants were briefed consistently about the aim of the study and how to interface with LstSim. They were informed about the nature of the tasks they would be performing, the data that would be collected, and how this data would be used.

Importantly, participants were informed that they could opt out of, and demand removal of their recorded data during the study at any time. This was to ensure that participants felt comfortable and in control throughout the study, in line with ethical guidelines for research involving human participants.

Figure 4: A single frame from the depth camera in our setup, pointed towards the operator, which can also be used to detect breathing patterns from the chest's movements [10]).

The participants' rights, privacy, and autonomy were respected throughout the study, and all data were handled confidentially and anonymously.

Due to technical issues encountered during data collection, one person's data had to be excluded. Therefore, the results presented in this paper are based on the data from 9 participants. The final participant group consisted of 4 females and 5 males. The age of the participants ranged from 26 to 36 years, with an average age of 30 years. Each participant was subjected to the same LstSim emergency control room simulation scenarios, and their breathing patterns were recorded throughout the simulation. The data collected from these participants formed the basis of our analysis and findings.

6 BREATHING MEASUREMENT

To measure the breathing patterns of the participants, participants wore the Go Direct Breathing Belt. This device is a non-invasive tool designed to measure human respiration. It is placed around the torso of the participant and works by measuring the force exerted as the torso expands and contracts during breathing. Additionally, the study participants also wore a smartwatch with PPG- and inertial sensors, and were observed through a depth camera to allow breathing detection [10] through alternative modalities (though these were not yet explored in the experiment section of this paper). The Go Direct Breathing Belt is equipped with a force sensor that records the expansion and contraction of the torso. As the participant inhales, the torso expands, exerting force on the belt, which is then recorded by the sensor. Conversely, as the participant exhales, the torso contracts, reducing the force on the belt. This continuous measurement of force provides a real-time, objective measure of the participant's breathing pattern. The use of the Go Direct Breathing Belt allowed us to collect high-resolution data on the participants' breathing patterns throughout the emergency control room simulations. This data was then analyzed to identify changes in breathing amplitude in response to varying levels of cognitive load.

7 RESULTS: COGNITIVE LOAD ASSESSMENT USING THE NASA TLX QUESTIONNAIRE

The NASA Task Load Index (TLX) is a widely used tool for evaluating perceived workload. Developed by the National Aeronautics and Space Administration, the NASA TLX is a multidimensional rating procedure that provides an overall workload score based on a weighted average of ratings on six subscales: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration1.

In our study, we applied the NASA TLX questionnaire after each simulation session to assess the cognitive load experienced by the participants. This approach allowed us to capture the changes in cognitive load as the participants transitioned from the learning and exploration session, through the routine operation session, to the high-intensity emergency operation session.

The results from the NASA TLX questionnaire provide a detailed picture of the cognitive load experienced by the participants across the three simulation sessions.

After the first session, which served as a learning and exploration phase, the NASA TLX scores were relatively low, as shown in the first boxplot. This suggests that the cognitive load during this session was manageable for most participants, likely due to the presence of tutorial hints and the absence of high-pressure emergency situations.

In the second session, which mimicked a routine operation environment, the NASA TLX scores increased, indicating a higher cognitive load. This is reflected in the second boxplot. Interestingly, the participants' confidence in their performance, as measured by the fourth question of the NASA TLX, dropped during this session. This may be due to the removal of tutorial hints, requiring participants to rely more heavily on their learned knowledge and skills.

The third session, which simulated emergency operations, resulted in a stark increase in NASA TLX scores, as shown in the third boxplot. This session, characterized by a high volume of calls and the need for rapid decision-making, induced a very high cognitive load in the participants. This is particularly evident in the responses to the questions about mental demand and temporal demand, which reflect the cognitive effort and time pressure associated with managing multiple emergencies simultaneously.

These findings highlight the significant cognitive load associated with switching between routine and emergency operations in a control room environment. They also underscore the importance of effective training and support systems in helping operators manage this load and maintain their performance and well-being.

8 BREATHING PATTERN RESULTS

A key component of our study involved the analysis of the raw amplitude of participants' breathing patterns. The results, as depicted in Figure 6, reveal a compelling aspect of individual variability in response to cognitive load.

Figure 6 illustrates the raw amplitude of breathing for each participant during the simulation. Each line in the graph represents a unique participant, with the x-axis denoting the time and the y-axis representing the amplitude of breathing. The graph clearly shows

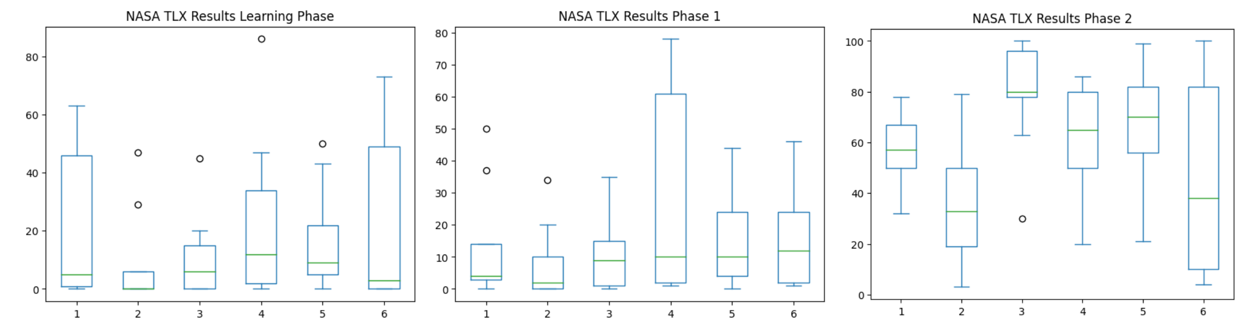

Figure 5: NASA TLX Results for the three experiment phases. The Questions refer to Question 1: Mental Demand, Question 2: Physical Demand, Question 3: Temporal Demand, Question 4: Performance, Question 5: Effort, Question 6: Frustration

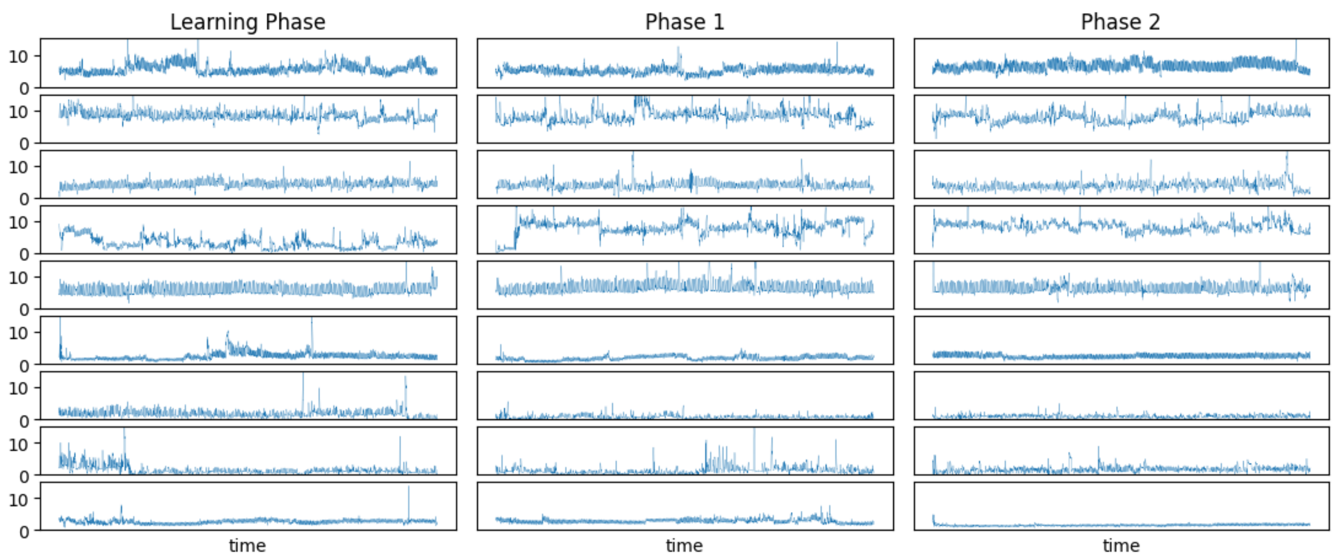

Figure 6: The raw sensor data as produced by the respiration belt, per participant and per simulation phase.

Study participant	1	2	3	4	5	6	7	8	9	All
Cohens d (P0 zu P1)	0.68	0.04	0.52	2.85	1.46	0.89	2.53	0.17	0.45	0.13
p-Wert (P0 zu P1)	**< 0.01**	0.86	**0.02**	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	0.44	**0.05**	0.07
Cohens d (P1 zu P2)	2.68	0.36	0.22	0.34	0.43	1.51	1.12	0.67	4.18	0.05
p-Wert (P1 zu P2)	**< 0.01**	0.11	0.34	0.13	0.06	**< 0.01**	**< 0.01**	**< 0.01**	**< 0.01**	0.54

Table 1: Statistical analysis of the amplitude changes between the experiment phases for each study participant individually and over all participants (far right column). The results show significant findings for most of the participants. Especially noteworthy is that significant results are accompanied by a large effect size.

a distinct pattern for each participant, with significant variations in both the amplitude and rhythm of breathing.

This finding suggests that the breathing response to cognitive load is highly individualistic and cannot be generalized across different operators. Each participant demonstrated a unique breathing pattern that was consistent throughout the simulation, despite the varying levels of cognitive load induced by the emergency control room scenarios.

This individual variability in breathing patterns under cognitive load underscores the complexity of using breathing as a measure of cognitive load. It suggests that any system designed to use breathing as a modality to measure cognitive load in control rooms would need to be personalized to each operator. This could involve a

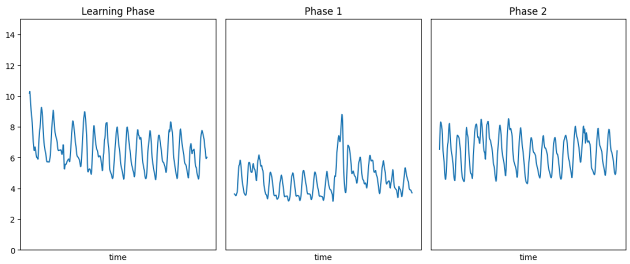

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Figure 7: A closer look at some examples of the breathing patterns present in the data from the respiration belt, across the three experiment phases. The X axes of the plots span about 60 seconds for each plot.

calibration phase where the system learns the operator's unique breathing pattern under different levels of cognitive load.

Despite the challenges posed by this individual variability, our findings also highlight the potential of breathing as a real-time, non-invasive measure of cognitive load. With further research and refinement, this could pave the way for more responsive control rooms that adapt to the operator's cognitive load, thereby enhancing performance and effectiveness.

Our analysis of the raw amplitude of participants' breathing patterns revealed not only individual variability but also a significant increase in amplitude as the cognitive load increased. The data, as shown in Table 1, provides a detailed breakdown of these changes.

On average, we observed a 6.5% increase in breathing amplitude between the Rest phase and Phase 1, a 7.8% increase between Phase 1 and Phase 2, and a substantial 13.08% increase between the Rest phase and Phase 2. These increases suggest a direct correlation between the cognitive load and the amplitude of breathing, with higher cognitive loads leading to more pronounced breathing patterns.

Table 1 presents the effect sizes (Cohen's d) and significance levels (p-values) for each participant's changes in breathing amplitude between the different phases. For most participants, the changes in amplitude were statistically significant between the Rest phase and Phase 1, as well as between Phase 1 and Phase 2. This indicates that the cognitive load induced by the emergency control room scenarios had a measurable impact on the participants' breathing patterns.

These findings further support the potential of using breathing amplitude as a real-time, non-invasive measure of cognitive load in emergency control room operators. They also highlight the importance of considering individual variability in breathing responses when designing systems to measure cognitive load.

9 DISCUSSION AND CONCLUSIONS

Interaction research in control rooms for critical processes, such as emergency dispatch centers, is notoriously difficult as *in situ* studies in such vital infrastructures is usually not allowed. As a result, the validity of simulation environments that allow a certain degree of immersion for studying natural interaction in control rooms remains an open question. In this work, we evaluated the cognitive load effects in particular for such a simulation environment, based on a large web-based simulator designed and played by professional operators. The results of our study provide compelling evidence that a simulated control room environment, such as the one created using LstSim, is successful in inducing cognitive load on participants. This is most pronounced by the significant changes in the NASA TLX survey results as the cognitive load increased across different phases of the simulation.

Our findings suggest that breathing patterns, specifically changes in breathing amplitude, can serve as a non-invasive modality to measure cognitive load in real-time. This has significant implications for the design and operation of emergency control rooms, potentially leading to the development of more responsive systems that adapt to the operator's cognitive load, thereby enhancing performance and effectiveness.

However, our study also revealed a high degree of individual variability in breathing patterns in response to cognitive load. This suggests that a one-size-fits-all approach may not be effective in using breathing as a measure of cognitive load. Additional research is needed to understand this individual variability better and to develop more generalized solutions that can accommodate different breathing patterns.

Furthermore, while our study recruited participants from the general population, future research should consider evaluating the simulation environment using domain experts, such as professional control room operators. This could provide more nuanced insights into the cognitive load experienced by emergency control room operators and the potential effectiveness of using breathing as a measure of cognitive load in this specific context.

In conclusion, our study represents an important step towards understanding and managing cognitive load in emergency control rooms. It opens up new avenues for research and highlights the potential of using physiological measures, such as breathing, to improve the design and operation of complex systems.

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