INVESTIGATING VIGILANCE FOR AUDITORY,

VISUAL, AND HAPTIC INTERFACES

IN ALARM MONITORING

By

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Bachelor of Science in Industrial Engineering and

Management

Oklahoma State University

Stillwater, OK

2022

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
May, 2023

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ACKNOWLEDGEMENTS

There are several people that I would like to thank that have helped me to get to where I am today. Firstly, I want to thank my advisor Dr. Katie Jurewicz for being an incredible advisor throughout my 3 years in the Human-Systems Engineering and Applied Statistics (HSEAS) Lab. She has truly taught me so much about the human factors field and its importance and applications in healthcare systems. Thank you for all your help in completing my thesis and assuring me that everything was going to work out. I would also like to thank my committee members, Dr. Camille DeYong and Dr. Joseph Nuamah, for their valuable feedback, guidance, and encouragement throughout this process.

I would also like to thank my lab mates, Matthew, Jimmy, and Ainsley, for all of their encouragement and help. I could not have finished this thesis without them. Special thank you to Ainsley for completing a participant study for me when I was unable to myself.

Lastly, I would like to thank my family and friends for all that you have done for me to be here. Thank you to my mom and dad for all the work that you have done for me to get to where I am today. Thank you to Hadley, Landon, and all my friends who have been by my side throughout my academic journey and life. I could not have done this without the support I have received from all of you.

Name: KYLIE DOWERS

Date of Degree: MAY, 2023

Title of Study: INVESTIGATING VIGILANCE FOR AUDITORY, VISUAL, AND HAPTIC INTERFACES IN ALARM MONITORING

Major Field: INDUSTRIAL ENGINEERING AND MANAGEMENT

Abstract: There are many alarms in healthcare systems that are primarily visual and auditory modalities. Alarms can occur thousands of times a day and can be stressful for clinicians. The overabundance of alarms leads to alarm fatigue. Alarm fatigue is a large patient safety issue as alarms may be silenced or not responded to in a timely manner. Introduction of a new information modality, such as a touchless haptic interface, could mitigate the effects of the vigilance decrement and alarm fatigue because of multiple resource theory and the idea that we have limited cognitive resources. The objective of this work is to investigate the use of a touchless haptic interface in an alarm monitoring vigilance task compared to visual and auditory interfaces. Data was collected on the reaction times of stimuli response to understand cognitive load and the number of correct detections, false positives, and false negatives to understand performance. Participants (N=36) completed a vigilance task in one of the three modality groups where they were asked to identify a stimulus over a 40-minute period. Mixed-effects linear regression models were built to analyze the differences between modalities and blocks. The main finding of this work is that visual interfaces perform best for alarm monitoring compared to auditory and haptic alarms; however, it was also shown that haptic interfaces may have a lower cognitive load compared to auditory interfaces. Therefore, haptic interfaces may be a promising avenue for offsetting information in healthcare alarm monitoring applications.

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CHAPTER I

INTRODUCTION

Healthcare environments contain many alarms that inform clinicians of a patient's health status (Solet & Barach, 2012). The most common alarms in healthcare settings are visual and auditory alarms. Auditory alarms can be played up to thousands of times for one patient in a day (Deb & Claudio, 2015; Mitka, 2013). For clinicians, the abundance and noise levels of alarms can be overwhelming and stressful (Lewandowska et al., 2020). Visual alarms are usually paired with auditory alarms to create a redundancy gain (Schlesinger et al., 2018). The overabundance of alarms can have a negative effect called alarm fatigue, which is the desensitization of alarms (Cvach, 2012). This can lead to clinicians ignoring or silencing alarms, which could potentially lead to patient harm (Deb & Claudio, 2015; Solet & Barach, 2012).

Monitoring alarms requires vigilance, or sustained attention, to ensure that the observer attends to all alarms (Szalma et al., 2004). The nature of long vigilance tasks requires a large cognitive workload and can lead to what is called the vigilance decrement (Warm, Parasuraman, & Matthews, 2008). The vigilance decrement is associated with decreased performance during a monitoring task after about 30 minutes (Warm, Parasuraman, & Matthews, 2008). In the case of monitoring alarms, clinicians may have a hard time identifying signals and could miss alarms which may lead to patient harm (Warm, Parasuraman, & Matthews, 2008).

Modalities, such as visual and auditory, support monitoring tasks, but they are often overused, and it may be helpful to offset information to a different modality (Ferris & Sarter, 2011). People have limited resources dedicated to information processing, so modalities have a limit on the number of cognitive resources they can be used for. Offloading information to another modality can reduce the cognitive load that could potentially lead to vigilance decrement and alarm fatigue (Ferris & Sarter, 2011). Touchless, 3D haptic systems could be a new avenue of information offloading (Brown et al., 2022; Carter et al., 2013; Iwamoto et al. 2008; Large et al., 2019). It is unknown if a touchless haptic system could be useful as an alarm interface and if it could mitigate alarm fatigue.

The objective of this research is to investigate the use of a touchless haptic alarm interface in comparison to visual and auditory modalities in a monitoring task. The research aims include: 1) to study the effect of alarm modality on monitoring performance and 2) to study the effect of alarm modality on cognitive load. Cognitive load was measured in terms of reaction times, and performance was measured in terms of correct and incorrect detections.

The experimental study had three different modality groups: visual, auditory, and haptic. Participants completed a vigilance task with four continuous 10-minute blocks, and participants were assigned and counterbalanced to visual, auditory, or haptic interfaces to identify alarms. The main finding of this work is that visual interfaces perform best for alarm monitoring compared to auditory and haptic alarms; however, it was also shown that haptic interfaces may have a lower cognitive load compared to auditory interfaces. Therefore, haptic interfaces may be a promising avenue for offsetting information in healthcare alarm monitoring applications.

CHAPTER II

REVIEW OF LITERATURE

Alarm Fatigue

In the healthcare system, patients are connected to many devices and technologies to continually track a patient's health status (Solet & Barach, 2012). Some of these devices are ventilators, infusion pumps, and monitors that serve as supervision or care delivery (Solet & Barach, 2012). The devices have alarms to notify nurses and physicians that a patient needs attention (Solet & Barach, 2012). In the ICU, alarms sound up to 350 times a day per patient (Ruskin & Hueske-Kraus, 2015). Nurses could hear thousands of alarms during a shift, and this overabundance of alarms across long shifts can lead to negative effects such as alarm fatigue (Schlesinger & Shirley, 2019).

Visual and auditory displays are the most prevalent in healthcare settings. Auditory alarms are found almost everywhere in patient care (Roche et al., 2021). The Joint Commission has found that there can be thousands of auditory alarms for a single patient in a day (Deb & Claudio, 2015; Mitka, 2013). With the large number of auditory alarms in departments like the ICU, it can be very loud and overwhelming for nurses. One study found the noise level was between 47 to 77 decibels in an ICU (Lewandowska et al., 2020; Vitoux, Schuster, & Glover, 2018). Long periods in this level of noise can be a large factor in stress and can further contribute to alarm fatigue (Lewandowska et al., 2020). Most of the alarms in the ICU are from the monitors and equipment, and the sounds can indicate that a patient needs attention or that equipment needs maintenance (Oliveira et al., 2018).

Visual alarms draw attention from patients to equipment and other devices to understand what information the alarms are indicating (Alirezaee et al., 2020). These alarms are usually paired with an auditory alarm to create a redundancy gain to catch the attention of healthcare providers (Schlesinger et al., 2018). Visual alarms typically utilize variance in color to indicate the different alarms (Cobus et al., 2018). For example, red alarms can indicate a high priority, yellow can indicate low priority alarms, and blue can indicate a technical error with the monitor (Cobus et al., 2018). Head-mounted displays, such as Google Glass, are newer technologies that are being implemented for visual alarms as they do not require the provider to move their head away from the patient to view the visual alarm (Cobus et al., 2018). However, this technology may not be suitable for sterile environments.

Although alarms are intended to improve quality of care and patient safety, there can be negative effects on patient safety due to the use and operation of monitoring equipment and its alarms (Oliveira et al., 2018). When alarms are ignored, the safety of patients is at risk (Solet & Barach, 2012). Alarms can lead to patient deaths if they are ignored (Deb & Claudio, 2015). In the United States, between January 2009 and June 2012, 82% of recorded incorrect responses or late responses to alarms resulted in patient deaths (Lewandowska et al., 2020; Purbaugh, 2014). In another case, nurses not hearing multiple low heart rate alarms led to another patient’s death when no nurses attended to the patient (Drew et al., 2014). After being asked if they had heard any alarms, none of the nurses could agree (Drew et al., 2014). Not only can the high number of alarms affect patients, but it can also be harmful to clinicians as the overabundance of alarms can intensify the already stressful conditions and reduce job performance (Ryherd et al., 2012; Schlesinger & Shirley, 2019).

The high number of alarms may lead to a negative effect, called alarm fatigue, for care providers. Alarm fatigue is the sensory overload and desensitization of alarms that lead to users not reacting to or realizing the instance of an alarm (Cvach, 2012). Alarm fatigue is prevalent in several industries including automotive, nuclear power, and aviation (Solet & Barach, 2012). Healthcare settings, such as the intensive care unit (ICU), have many alarms that can overwhelm clinicians, hinder decision-making skills, and reduce awareness of their surroundings (Deb & Claudio, 2015). False alarms and constant occurrences of alarms lead to sensory overload for nurses (Storm & Chen, 2021). A consequence of alarm fatigue is clinicians turning off alarms rather than responding correctly to them (Solet & Barach, 2012). In a survey by Christensen et al., 2014, 93% of nurses agreed that alarm fatigue leads to silencing noises. The consequences of alarm fatigue are so large in the United States it was considered one of the top ten medical technology hazards in 2012 (Cho, Kim, Lee, & Cho, 2016; ECRI Institute, 2011). In 2014, the Joint Commission set alarm fatigue as the national patient safety goal for 2015 due to its concern and negative effects on patients and staff (Storm & Chen, 2021).

Along with the high noise level of alarms, false alarms and their misinterpretation are contributing factors to alarm fatigue (Cvach, 2012; Storm & Chen, 2021). According to Schelsinger & Shirley (2019), studies have shown that over 75% of alarms are false alarms and add to the overabundance of sounds and alarms. In another survey, 81% of nurses mentioned that the overuse of false alarms leads to alarm fatigue (Christensen et al., 2014). False alarms can happen from patient-care activities like moving the monitoring equipment (Solet & Barach, 2012). Another factor of false alarms is that it can lead to the 'cry wolf' effect where nurses start identifying most or all alarms as false (ECRI Institute, 2007; Sendelbach, 2012). Nurses will then not respond to alarms, or not identify alarms at all. The effects of false alarms have sparked interest in research to mitigate alarm fatigue (Cvach, 2012; Storm & Chen, 2021).

Vigilance

The monitoring of alarms is considered a vigilance task that requires the attention of the clinician over a long period of time. Vigilance, also known as sustained attention, is keeping attention on a task for a prolonged period (Davies & Parasuraman, 1982; Peltier et al., 2022; Shaw et al., 2006). Sustained attention is required to recognize and detect signals or changes in tasks (Shaw et al., 2006). Vigilance tasks are typically continuous and require the identification of signals. Alarms that can be unpredictable or rare and require few and random responses, such as patient care (Davies & Parasuraman, 1982; Greenlee, DeLucia, & Lui, 2022; Warm, 1984; Warm & Jerison, 1984). These tasks can even be considered "mentally undemanding" or asking users to pay attention to simple assignments (Warm, Parasuraman, & Matthews, 2008).

Despite its undemanding appearance, vigilance requires a heavy workload and designs centered around vigilance need to take that into account (Szalma et al., 2004). It has been reported by observers that participants after long vigilance tasks are bored, annoyed, tired, and overworked (Szalma et al., 2004; Warm, 1993). Vigilance tasks require large workload demands from users and can be stressful, especially if the consequences of a miss or incorrect detection are large (Warm, Parasuraman, & Matthews, 2008). According to Hart and Staveland (1988), vigilance assignments require temporal, physical, and mental demands. The three demands interact and result in overall performance, frustration, and effort (Hart & Staveland, 1988).

Specialists in human factors and ergonomics are interested in vigilance because of its importance in different jobs and daily tasks (Shaw et al., 2006). For example, vigilance tasks are used at airports with air traffic controllers and with Transportation Security Administration (TSA) bag inspections (Davies & Parasuraman, 1982; Hancock & Hart, 2002). Vigilance is needed when driving a car to prevent car accidents and follow traffic rules (Peltier et al., 2022). A lack of vigilance while driving leads to low concentration and slow reactions to obstacles in the road, veering into the wrong lane, and many other causes of accidents. Manufacturing plants require attention to operate machinery and watch for problems in the production lines (Peltier et al., 2022). Even the military requires vigilance to watch satellite image surveillance and monitor security risks (Peltier et al., 2022). It is also critical in healthcare settings where alarms are common and need to be responded to, like in surgical operations (Daly & Wilson, 1993; Gill, 1996; Weinger & Englund, 1990). It is important during surgery to watch anesthesia gauges or in cytological screening (Daly & Wilson, 1993; Gill, 1996; Weinger & Englund, 1990). Because vigilance tasks can seem mentally undemanding but last long periods of time, there can be a decrement in performance. Therefore, they can require many cognitive resources (Parasuraman & Mouloua, 1987; Warm, Parasuraman, & Matthews, 2008).

As vigilance tasks, such as alarm monitoring, become harder to perform over time, vigilance decrement starts to manifest (Warm, Parasuraman, & Matthews, 2008). Vigilance decrement is the decline of detection performance after about 30 minutes of a sustained attention task (Warm, Parasuraman, & Matthews, 2008). It makes detection tasks more difficult for individuals, worsens their ability to correctly identify signals, and results in an inefficient performance (Helton & Warm, 2008; Warm et al., 2015). A vigilance decrement results in a performance decrement (Al-Shargie et al., 2019). In healthcare settings, most alarms are visual or auditory, and the vigilance decrement can occur within both visual and auditory modalities (Davies & Parasuraman, 1982; See et al., 1995). Broadly, it has been shown in studies across several industries that auditory alarms lead to better performance over long periods of time than visual alarms (Warm & Jerison, 1984). There is a higher accuracy and higher sustained attention when implementing auditory alarms than when only using visual alarms (Davies & Parasuraman, 1982; Warm & Jerison, 1984).

Multiple Resource Theory and Tactile Offloading

Offsetting information to different modalities can help mitigate the vigilance decrement and can be explained through multiple resource theory (MRT; Wickens, 2008). The MRT model shows that people have limited resources for information processing and describes how information can be presented in various modalities for perceptual and cognitive processing (Wickens, 2008). For example, driving is a visual-spatial task to navigate a vehicle and avoid obstructions in the road. Driving can also involve verbal tasks such as voice commands or talking to someone on the phone. If the driver wants to look at the radio to change the station or look at a touchscreen, visual resources are competing with the primary task of driving; however, a driver can listen to the radio with little impact on driving as the auditory and visual resources do not compete. MRT separates how we can identify information and tasks based on the modality. A figure based on the multiple resource model proposed by Wickens (2008) is shown in Figure 1. If tasks are utilizing the same cognitive resources (i.e., if they are in the same block in Figure 1), there will be a performance decrement, similar to the decrement seen in a vigilance task. We must allocate resources so that tasks do not have a performance decrement. Therefore, if multiple auditory or visual alarms are competing for the same cognitive resources, a vigilance decrement may occur. An abundance of auditory and visual alarms, which are found in healthcare systems, can lead to cognitive overload and require offloading to other modalities to lighten the burden (Ferris & Sarter, 2011). Introducing a new modality, such as tactile devices, can be a way to lighten the cognitive resources caused by the other modalities.

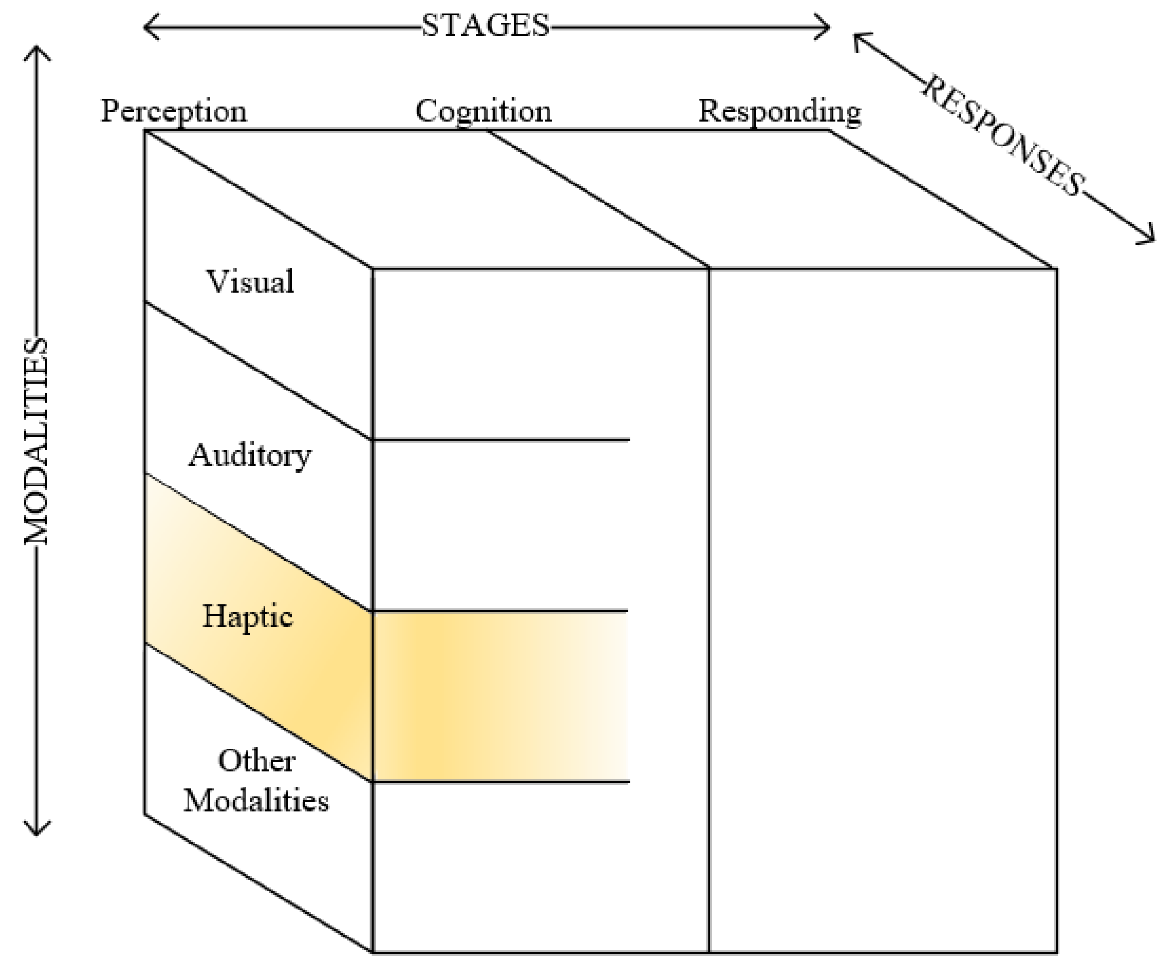

Figure 1. Modified and adapted from Multiple Resource Theory Model (Wickens, 2008)

Introducing different alarm modalities has been a new avenue of research to mitigate alarm fatigue in several industries. Tactile modalities have been studied to see if they would improve alarm fatigue and responses to alarms. Vibrotactile alarms are useful in places with auditory or visual clutter or if private displays are needed (Jones & Sarter, 2008). Vibrotactile displays have been used as alarms in several areas, such as transportation. For example, vibrotactile cues have been studied to assist drivers in avoiding front- and rear-end accidents instead of using a visual display (Ho, Reed, & Spence, 2006). Implementing the vibrotactile cues decreased reaction times compared to only visual cues when responding to front-to-rear-end accidents (Ho, Reed, & Spence, 2006). Also, implementing vibrotactile cues or auditory alarms for lane-keeping assist is a popular feature added into vehicles that do not compete with a driver's visual resources (Spence & Ho, 2008). The use of a tactile modality for driving, rather than a visual alarm, is preferred because visual resources are necessary for safety in the primary task of driving.

In healthcare, tactile alarms have been studied and shown positive results (McLanders, Santomauro, Tan, & Sanderson, 2014). Ferris and Sarter (2011) studied the use of tactile displays to reduce the visual and cognitive resources used by anesthesiologists. They discovered that tactile offloading could be beneficial in high visual and auditory demanding settings (Ferris & Sarter, 2011). The use of a hybrid display reduced the time it took to complete anesthesiology tasks and assess pulse oximetry (Ferris & Sarter, 2011). McLanders and colleagues (2014) studied the use of tactile devices along the arm to check heart rate arterial blood oxygen saturation (McLanders, Sanotmauro, Tan, & Sanderson, 2014). They found that vital signs could be accurately identified at a faster rate (McLanders, Sanotmauro, Tan, & Sanderson, 2014). However, in a study conducted by Delucia and Greenlee (2022), it was found that tactile displays can be demanding and can reduce how well someone can identify an alarm. Despite the interest in tactile alarms, alarm fatigue remains an issue. Additionally, tactile sensors are invasive to the end user; therefore, other modalities that are less invasive to users should be explored as a means of offsetting cognitive resources.

Haptic Modality

According to multiple resource theory, it is advantageous to offset alarms to other modalities and one modality that has not been studied significantly is touchless haptic displays. Touchless, 3D haptic interfaces are mid-air, ultrasounds that allow a new form of human-computer interaction (Brown et al., 2022; Carter et al., 2013; Iwamoto et al. 2008; Large et al., 2019). It sends an output to the user without having to touch a physical surface (Brown et al., 2022). There are many compelling reasons for implementing haptic systems into the healthcare system. Firstly, they are not intrusive to the physical environment of the user (Paneva, Seinfeld, Kraiczi, & Müller, 2020). They are also more sanitary since no surfaces are contacted; therefore, no surface contamination can be spread (Paneva, Seinfeld, Kraiczi, & Müller, 2020). Haptic displays are advantageous compared to more conventional human-computer interaction interfaces such as touchscreens because touchscreens are subject to damage, prone to contamination spread, often unreachable, and unviewable due to prolonged use (Corenthy et al., 2018; Davies, Clinch, & Alt, 2014). 3D haptic displays are not subject to the same negative effects because they are touchless and can be used from a distance (Corenthy et al., 2018). There are even several advancements in haptic feedback where users can additionally feel texture and temperature (Kim, 2022; Rakkolainen et al., 2020). These sensations can help with distinguishability that cannot be output with current touchscreen technology.

Some studies have looked at implementing 3D haptic displays in industries outside of healthcare. A study looked at implementing haptic to output braille as a hygienic way to give information to the blind population (Paneva, Seinfeld, Kraiczi, & Müller, 2020). Other studies have looked into making mall kiosks with a digital display, haptic output, and gesture control to mitigate germ spread and damage to equipment (Corenthy et al., 2018). This could be a new avenue for advertising and interactive displays in public settings (Corenthy et al., 2018). Another area haptic has been studied is in the automotive industry. Head-up displays in vehicles that utilize haptic buttons are accepted more than systems with 3D touchless gestures or hands-free voice commands (Betancur et al., 2018). However, the haptic system in this study did also use visual and audio feedback while using a haptic input system (Betancur et al., 2018). As haptic displays are implemented, it is suggested that the design of haptic icons needs to be "distinguishable, learnable, salient, and recognizable" (MacLean, 2008, p.87; Brown et al., 2022).

Similarly to how visual and auditory alarms were offset to tactile alarms in healthcare settings, haptic systems can be a new avenue to study alarm fatigue for healthcare applications. Multiple resource theory shows that we need to offload resources if others are being overloaded. In departments like the ICU, there are many auditory and visual alarms that can overload the clinician. Therefore, offloading to a haptic system could decrease the risk of sensory overload. The cognitive resources that are being occupied by visual and auditory alarms can be freed up. Monitoring patient alarms is a vigilance task, and as a vigilance decrement begins to occur, so does alarm fatigue. Studying haptic alarm systems as a new output modality can mitigate alarm fatigue.

Research Objective, Aims, and Hypotheses

The objective of this research is to investigate the use of a touchless haptic alarm interface in comparison to visual and auditory modalities in a monitoring task. The research aims include: 1) to study the effect of alarm modality on monitoring performance and 2) to study the effect of alarm modality on cognitive load. Cognitive load was measured in terms of reaction times and performance was measured in terms of correct and incorrect detections.

CHAPTER III

METHODOLOGY

An experimental study was performed to investigate a vigilance monitoring task to study the effect of alarm modality on performance and cognitive load. The Oklahoma State University Institutional Review Board gave this study an exempt status (IRB-23-99-STW; Appendix A).

Study Design

The primary independent variable in this study was alarm modality. Participants were assigned to either the visual, auditory, or touchless haptic alarm conditions. The dependent variables were performance and cognitive load. Performance was measured via correct and incorrect detections (Research Aim 1), and cognitive load was measured through reaction times in seconds (Research Aim 2). Each participant, regardless of alarm modality, performed a vigilance monitoring task in four continuous 10-minute blocks, similar to previous vigilance studies (Greenlee, DeLucia, & Lui, 2022; McIntire et al., 2014). Block number was an additional independent variable to alarm modality. Therefore, this is a mixed methods design where alarm modality is a between-subjects variable, and experimental block is a within-subjects variable.

Participants

Participants (N=36) were recruited in Stillwater, OK to participate in the study. Participant eligibility included that their ages should be within 18-64 years old, and that they should be able to read write, and speak in English. The participants had to be able to have full manual dexterity of their hands and wrists. Participants also had to have normal or corrected vision, normal or corrected hearing, and no history of peripheral neuropathy. They were also asked to not intake any stimulant or depressant drugs within 12 hours before the study (i.e., caffeine, alcohol, etc.). They were screened prior to the study to ensure they were eligible Participants were assigned to a visual modality group, auditory modality group, or haptic modality group upon their arrival at the lab. The groups were counterbalanced by randomly ordering the modalities so that after every three participants there were an equal number of participants per group. Participants received compensation of a $10 gift card for one hour of their time.

Apparatus and Experimental Setting

The study took place in the Human-Systems Engineering and Applied Statistics (HSEAS) Lab at Oklahoma State University.

For the visual modality group, a Microsoft PowerPoint was presented on a Dell 24 P419HC monitor. This test was similar to the Multiple Vigilance Test (MVT) used in a study by Hirshkowitz, De La Cueva, and Herman (1993). A visual stimulus appeared every 2 seconds (Shown in Figure 2). During the two seconds between the stimuli, a solid black box was presented. The stimuli remained on the screen for 500 milliseconds (ms). In each 10-minute block, seven alarms played instead of the non-alarm stimuli. The shapes were solid black with a white background to ensure high contrast.

In the auditory modality group, an adaptation of the Wilkinson Auditory Vigilance Test was used (Wilkinson, 1968). Every two seconds, a 1000 hertz tone was played at 60 dB to simulate alarms and false alarms in the ICU (Lewandowska et al., 2020; Vitoux, Schuster, & Glover, 2018). In each 10-minute time block, 233 tones at 500 ms were played to indicate false alarms, and seven detectable shorter tones at 300 ms were played to indicate alarms. The sounds were sequenced using Microsoft PowerPoint.

The haptic modality group utilized an Ultraleap haptic system (see in Figure 3; www.ultraleap.com/haptics/) that uses ultrasound speakers to create a tactile feeling without being in contact with the output surface. In this group, participants were instructed to leave their non-dominant hand over a hole in a table that the haptic system was underneath. Every two seconds, a haptic display occurred that lasted 500 ms or 300 ms. In each 10-minute time block, 233 displays that were 500 ms in length were played to indicate a false alarm, and seven detectable shorter displays at 300 ms were played to indicate an alarm. Participants used their non-dominant hand over the haptic system and their dominant hand to press the spacebar at the instance of an alarm.

For all groups, a detection of an alarm required the participant to click the spacebar on a keyboard which recorded reaction times. There were four continuous 10-minute blocks with seven alarms in each block for all modality groups (shown in Figure 4). The alarms were presented at the same time for each of the modalities so that there was not a risk of variability in alarm presentation and was not a possible factor if there were differences in vigilance decrements between modalities. The alarms were ordered in each group using R (v4.2.1, R Core Team 2022) and selecting a random seed to order seven alarms and 233 non-alarms in each block.

All participants were recorded with an Intel® RealSense™ D435 camera (Intel Corporation, Santa Clara, CA). This allowed for any discrepancies in the data to be analyzed after the study.

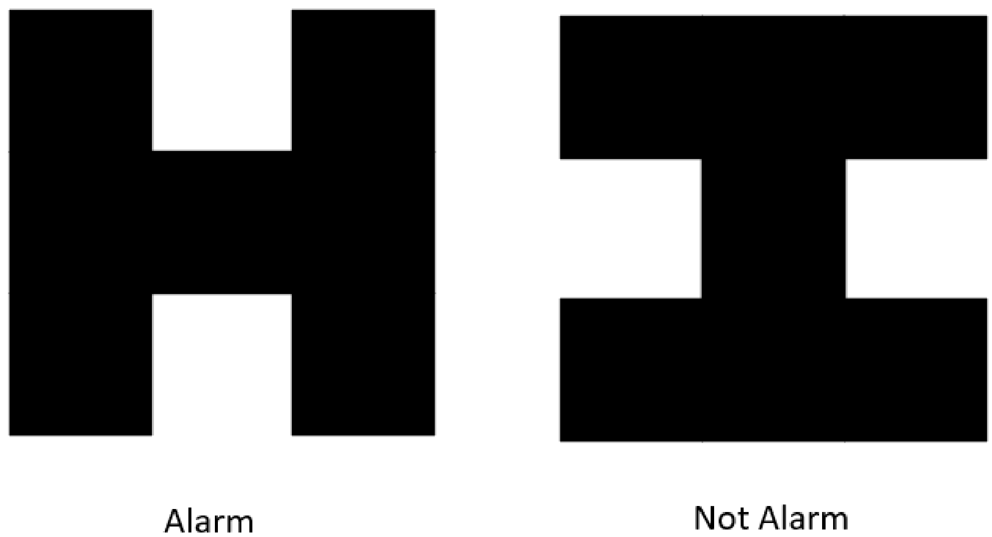

Figure 2. Visual stimuli

Figure 3. Ultraleap haptic system

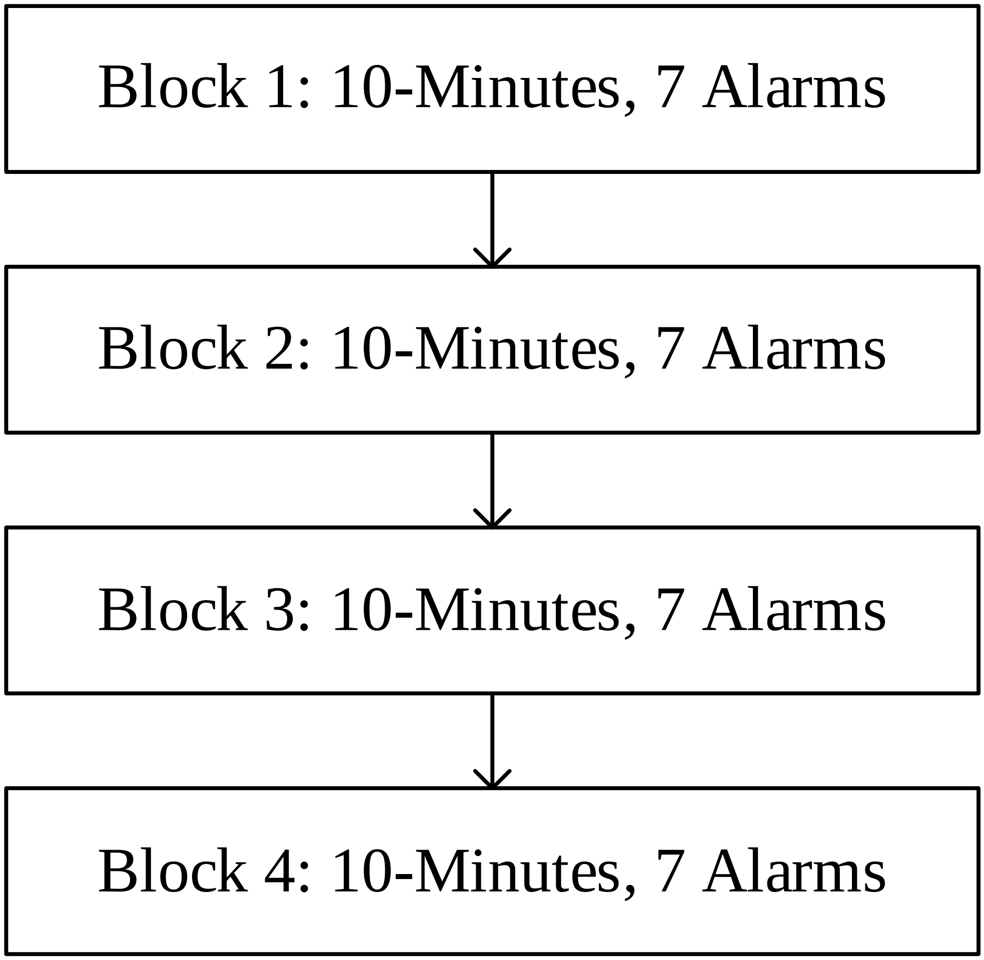

Figure 4. Study design

Procedure

The participants underwent a screening upon arrival to the lab to confirm that they were able to complete the task related to their pre-assigned modality. For the visual modality, they had to be able to see and identify the differences in the shapes of the stimuli. For the auditory modality, they had to be able to hear and identify the different lengths of the tones. For the haptic modality, they had to be able to feel and identify the different lengths of the haptic displays. If they passed the screening, the informed consent process was conducted. Once the consent form was signed, the participant was asked to complete a demographic survey. The researcher reviewed the experimental process with the participant, and then the participant was seated at the monitoring station after they had a chance to ask questions.

Before beginning, the participants were informed that they will press the spacebar on the keyboard when they identified the alarm stimuli relevant to their assigned modality. Visual participants completed the task adapted from the MVT after understanding the procedures (Hirshkowitz, De La Cueva, & Herman, 1993). There was no practice session as a practice session may have influenced the quantification of performance over time due to the vigilance decrement of 30 minutes (Warm, Parasuraman, & Matthews, 2008).

Participants in the auditory group completed the task adapted from the Wilkinson Auditory Vigilance Test (Lieberman, Coffey, & Kobrick, 1998; Wilkinson, 1968). Participants were informed to press the spacebar on the keyboard when they identified the auditory alarm, which was the 300 ms tone. Like the visual condition, there was no practice session.

Participants in the haptic group placed their hands over a hole in the table that was aligned with the haptic output. They were able to rest their arm on the table so that their arm and wrist were not strained. The participants were informed to press the spacebar on the keyboard when they identified an alarm, which was the 300 ms display. Participants in the haptic group left their hand over the circular hole of the table, therefore there was no risk of hand movement and not being able to feel the output of the haptic display due to displacement (see Figure 6). Like in the auditory and visual groups, there was no practice session.

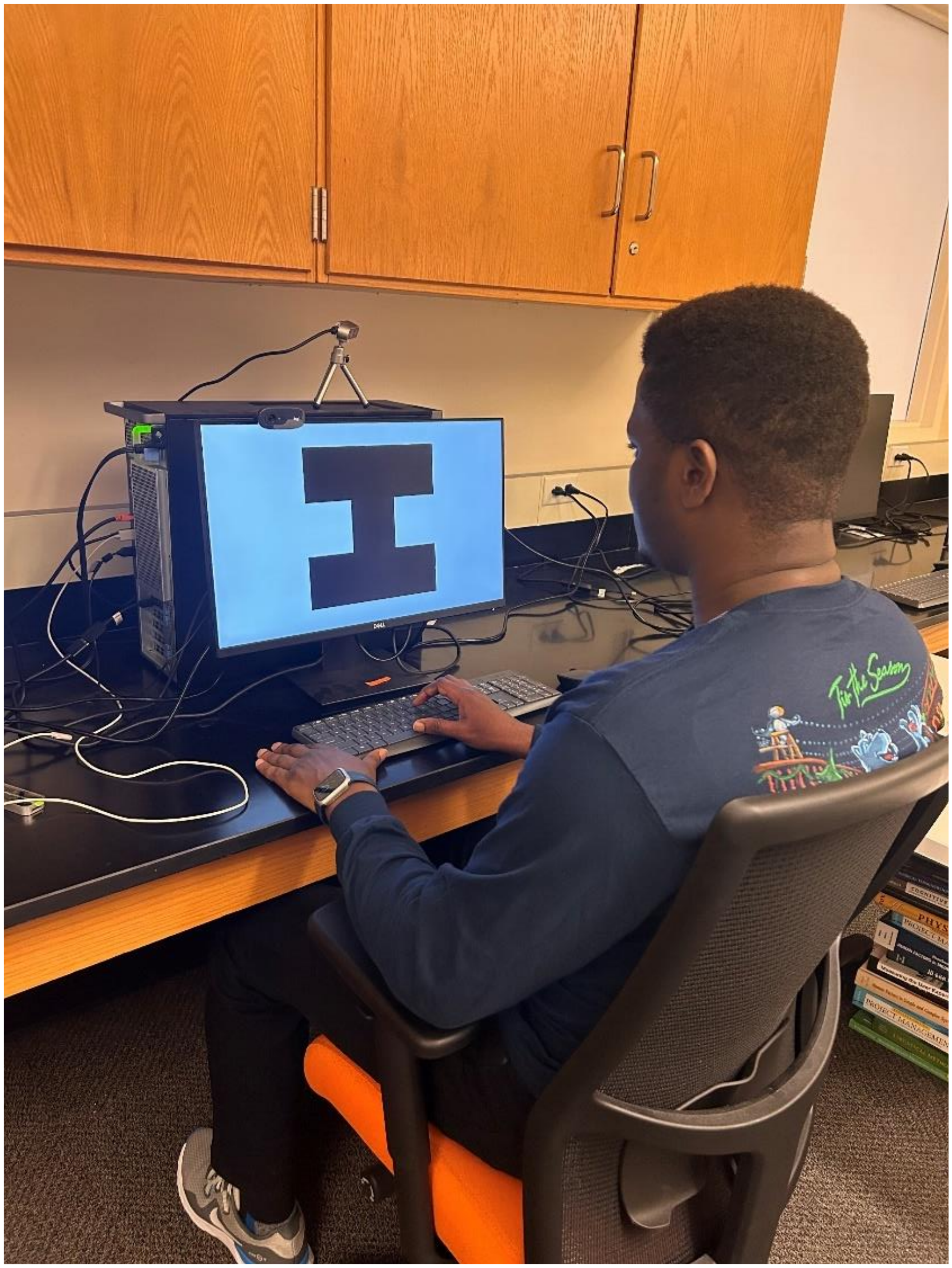

Figure 5. Visual modality experimental session participant setup

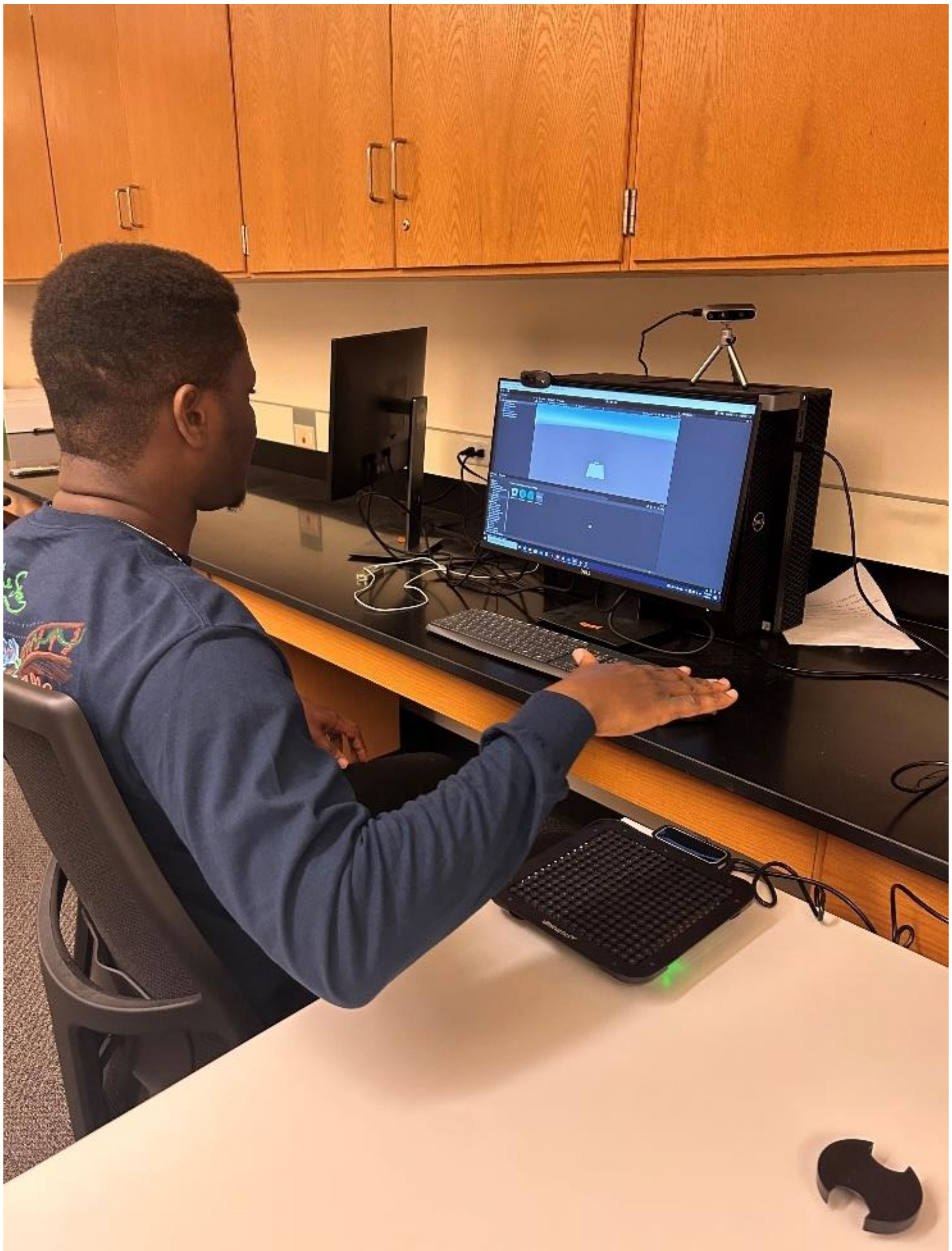

Figure 6. Haptic modality experimental session participant setup

Each study ran for 40 minutes total with four continuous 10-minute monitoring blocks. In each of the 10-minute blocks, there were seven alarm signals and 233 non-alarm signals. There were equal alarms in each block so that when they were compared, the number of alarms cannot be a factor in the vigilance or performance decrement. Participants were not informed of the different time blocks so that there were no unnecessary interruptions that could have affected the vigilance task. All participants were asked to silence their personal electronic devices and to remove any watches that would have allowed them to know how long the study had lasted. Participants knowing how much time had passed could have affected how they felt towards the study and therefore affected how they reacted to the alarms over time.

After completion of the study, the participants completed an informal interview. They were asked questions related to the difficulty and fatigue of the task. Participants were then debriefed and given their compensation.

Data Collection

Performance was measured for Aim 1, and cognitive load was measured for Aim 2. To study performance, correct detections, false positives, and false negatives were recorded by the researcher. This data was collected separately for each block. To study cognitive load, reaction times were collected. Reaction time was measured in seconds from the time an alarm was presented to the participant to when they clicked the spacebar to indicate an alarm had been detected. If a participant did not react to an alarm, it was noted as a false negative and no reaction time was recorded. Likewise, if the participant reacted to a non-alarm stimulus, then it was noted as a false positive and no reaction time was recorded.

Data Analysis

Aim 1

The number of correct detections, false positives, and false negatives were analyzed to study performance between the different alarm modalities. False positives and false negatives can be a sign of alarm fatigue in participants (Cvach, 2012; Storm & Chen, 2021). A sample table for recording counts for each participant is shown in Table 1. Since correct detections, false positives, and false negatives are all correlated, a multivariate approach should be used to analyze the data (Rencher, 2002). Additionally, since there are fixed and random effects in the experiment, a mixed-effects approach should also be utilized. However, it is very difficult to model multivariate mixed-effects data, and there are no frequentist statistical approaches that can handle multivariate multilevel modeling (Hadfield, 2010; Hadfield, 2015). The only option for studying multivariate mixed models is to take a Bayesian approach.

Bayesian approaches have been performed in the past for multivariate mixed data; however, the models are difficult to build and are out of scope of this thesis. Therefore, this thesis takes a univariate approach where correct detections, false positives, and false negatives are analyzed separately. A univariate approach is a limitation of the study and thus may have an inflated alpha for results; however, since this study is exploratory and the first of its kind, an inflated alpha will ensure that no findings are missed in the data. Therefore, three mixed-effects linear regression models will be built for correct detections, false positives, and false negatives. Since the data is counts, a Poisson distribution family will be used for the regression models. However, it is anticipated that the assumption that mean equals the variance for Poisson regression will be violated; therefore, a negative binomial distribution family may be used. Modality and block will be fixed effects, and participant ID will be a random effect. Because each participant is different, they will add an unexplained variance to the data that can be adjusted by the random effect (Snijders, 2005).

Tukey contrasts were then performed separately for modality and block to analyze all pairwise comparisons. All data analysis was performed in R (v4.2.1, R Core Team 2022). The functions used were the *glmer.nb* function of the lme4 package (Bates et al., 2015), the *glht* function of the multcomp package (Hothorn, Bretz, & Westfall, 2008), the *cooks.distance* function of the influence.ME package (Nieuwenhuis, te Grotenhuis, & Pelzer, 2012), and the *pbg* function of the profileR package (v0.3-5; Bulut & Desjardins, 2018).

Table 1. Count data for Aim 1

	Correct Detections (Out of 7)	False Positives (Out of 233)	False Negatives (Out of 7)
Block 1			
Block 2			
Block 3			
Block 4			

Aim 2

Reaction times to alarms were analyzed to study the differences in cognitive load between different alarm modalities (Horsky, Kaufman, Oppenheim, & Patel, 2003). Longer reaction times can indicate a high cognitive load. The times were recorded in Microsoft Excel from when the alarm starts to when the participant reacts to an alarm (i.e., hitting the space bar). If the participants missed an alarm, no time was recorded. A mixed-effects linear regression model was used to analyze reaction time where reaction time in seconds will be the output of the model. The inputs to the regression model will be block and alarm modality as fixed effects and participant ID as a random effect. Participant ID is a random effect to control for the within-variability of each participant. After the model was fit, the assumptions of normality, homoscedasticity, linearity, no outliers or influential points, and no multicollinearity issues were checked. To check for linearity and homoscedasticity, residual plots were checked for no curvature and no pattern respectively. Normality was checked on a normal Q-Q plot. The presence of outliers was evaluated by looking at a residual versus leverage plot. To address for multicollinearity issues, any predictor variable with a variance inflation factor (VIF) greater than five was removed. Influential points in the data were checked by calculating Cook's distance (Cook, 1977). All data analysis was performed in R (v4.2.1, R Core Team 2022). The *lmer* function was used of the lme4 package (Bates et al., 2015), and the *vif* function was used of the car package (Fox & Weisberg, 2019).

CHAPTER IV

FINDINGS

Demographics

Participants (N=36) were 19 to 23 years of age (*M*=20.917, *SD*=1.317). Eighteen participants identified as female, 17 identified as male, and 1 identified as non-binary. The visual group had an equal number of males (n=6) and females (n=6). The auditory group had more females (n=8) than males (n=4). The haptic group had more participants identified as male (n=7) than female (n=4) and non-binary (n=1). Most of the participants were students majoring in a science or engineering area (n=20).

Aim 1: Performance

Aim one analyzes performance based on the number of correct detections, false positives, and false negatives for the modalities and blocks.

Average Counts

The total correct detections, false positives, and false negatives for each modality group and block are shown in Tables 3, 4, and 5 respectively. When looking at the average correct detections per modality in Table 3, the visual group had a higher overall average compared to the auditory and haptic groups. In all groups, the average correct detections decreased from block 1 to block 4. In Table 4, average false positives were lowest for the visual group. The haptic group had the highest overall average for false positives. The visual group had the lowest average for false negatives, followed by auditory, and then haptic (Shown in Table 5).

Table 2. Characteristics of study participants

Variable Name	N (%)	Visual	Auditory	Haptic
Age	M=20.92 SD=1.32	M=21.25 SD=1.31	M=20.58 SD=1.25	M=20.92 SD=1.26
Gender				
Male	18 (50)	6 (50)	4 (33.3)	7 (58.3)
Female	17 (47.2)	6 (50)	8 (66.7)	4 (33.3)
Non-binary	1 (2.8)	0 (0)	0 (0)	1 (8.3)
Education, area of study				
Science or Engineering	20 (55.6)	8 (33.3)	7 (58.3)	5 (41.7)
Not Science or Engineering	16 (44.4)	4 (66.7)	5 (41.7)	7 (58.3)
Caffeine Intake				
0 Times a Day	14 (38.9)	4 (33.3)	4 (33.3)	6 (50)
1 Time a Day	14 (38.9)	5 (41.7)	5 (41.7)	4 (33.3)
2-3 Times a Day	8 (22.2)	3 (25)	3 (25)	2 (16.7)
Average Sleep per Night				
4-6 Hours	8 (22.2)	5 (41.7)	0 (0)	3 (25)
7-9 Hours	28 (77.8)	7 (58.3)	12 (100)	9 (75)

Table 3. Average count of correct detections

Block	Visual	Auditory	Haptic
1	7.00	6.58	6.42
2	6.83	6.58	6.17
3	6.25	6.00	5.25
4	6.75	6.25	4.67

Table 4. Average count of false positives

Block	Visual	Auditory	Haptic
1	0.83	22.25	25.58
2	0.17	12.08	11.92
3	0.08	9.33	14.83
4	0.17	16.42	11.33

Table 5. Average count of false negatives

Block	Visual	Auditory	Haptic
1	0.00	0.42	0.58
2	0.17	0.42	0.83
3	0.75	1.00	1.83
4	0.25	0.75	2.33

Profile Plots

Profile plots for average correct detections, false positives, and false negatives are shown in Figures 7, 8, and 9. The modalities generally had a decrease in correct detections over time. For false positives, haptic and auditory modalities generally decreased over time. The visual modality was consistent for false positives. All modality groups had an increase in false negatives over time. The haptic group had the largest increase of false negatives and decrease of correct detections.

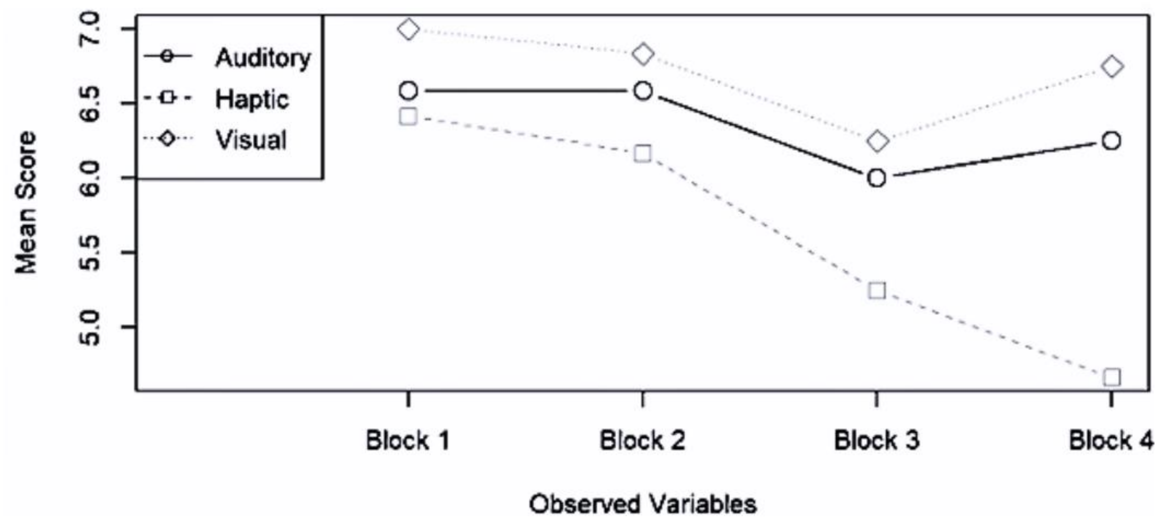

Figure 7. Correct detections profile plot

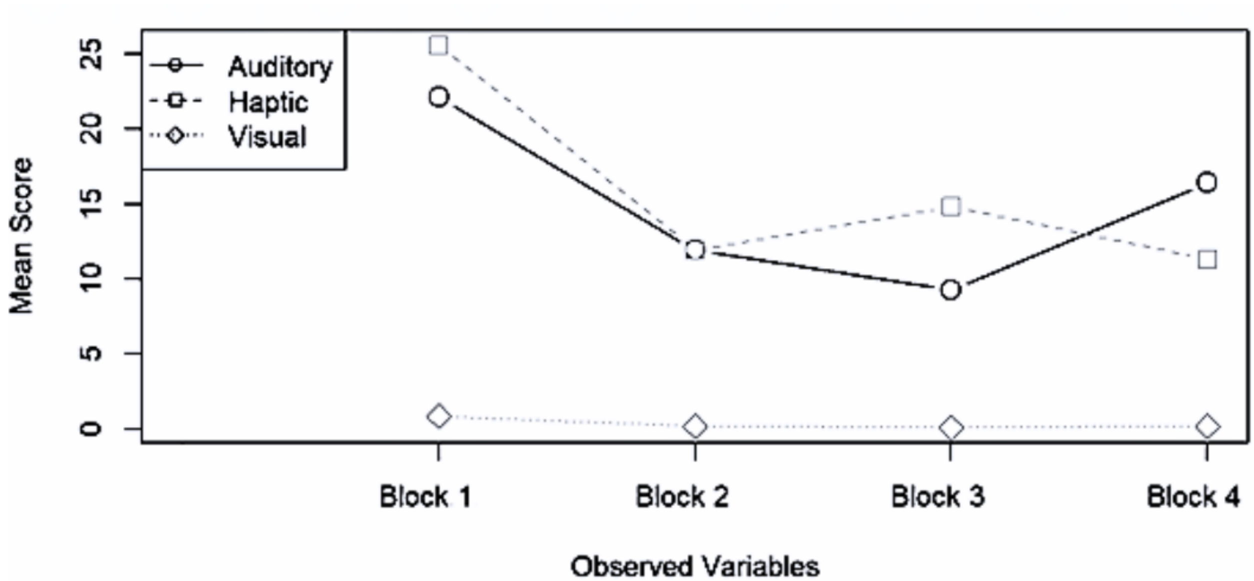

Figure 8. False positives profile plot

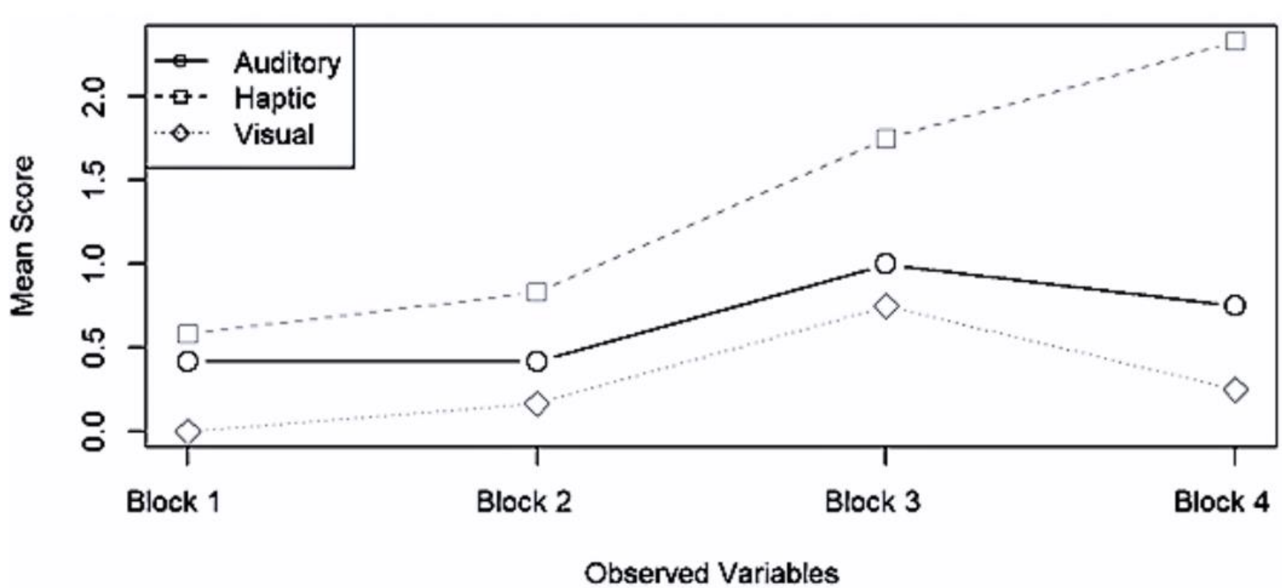

Figure 9. False negatives profile plot

Mixed-Effects Models

The data for the counts per block is multivariate and longitudinal. It is not possible to perform a mixed-effects multivariate model, so three univariate negative binomial mixed-effects linear regression models were created with the random effect of participant ID and fixed effects of modality and block. The models for correct detections, false positives, and false negatives are shown in Tables 6, 7, and 8 respectively. For the correct detection model, there were no significant differences between the haptic modality and auditory modality. There was also no significant difference between the visual modality and the auditory modality. There were no significant differences between blocks 1 and 2, blocks 1 and 3, and blocks 1 and 4. For the false positives mixed-effects model, the visual modality was significantly lower in comparison to the auditory modality group. Also, blocks 2, 3, and 4 each had significantly less false positives than block 1. For false negatives, no modalities were significantly different from the auditory modality, but blocks 3 and 4 each had a significantly greater number of false negatives than block 1.

Table 6. Mixed-effects model for correct detection data

	β	**SE**	**z**	**P>|z|**
(Intercept)	1.917	0.073	26.173	<0.001*
Haptic	-0.122	0.080	-1.525	0.127
Visual	0.054	0.078	0.699	0.484
Block 2	-0.021	0.086	-0.244	0.807
Block 3	-0.134	0.091	-1.469	0.142
Block 4	-0.124	0.090	-1.380	0.168

Table 7. Mixed-effects model for false positive data

	β	**SE**	**z**	**P>|z|**
(Intercept)	2.335	0.512	4.564	<0.001*
Haptic	0.530	0.703	0.753	0.451
Visual	-3.005	0.777	-3.866	<0.001*
Block 2	-1.809	0.311	-5.824	<0.001*
Block 3	-2.120	0.329	-6.444	<0.001*
Block 4	-2.147	0.327	-6.559	<0.001*

Table 8. Mixed-effects model for false negative data

	β	**SE**	**z**	**P>|z|**
(Intercept)	-1.6434	0.434	-3.789	<0.001*
Haptic	0.805	0.442	1.822	0.068
Visual	-0.842	0.512	-1.634	0.100
Block 2	0.348	0.370	0.940	0.347
Block 3	1.276	0.320	3.992	<0.001*
Block 4	1.204	0.323	3.731	<0.001*

Tukey Contrasts

Tables 9, 10, and 11 show the Tukey HSD contrasts between modality for correct detections, false positives, and false negatives. No modalities were significantly different for correct detections. The visual group was significantly lower in false positives than the auditory group. The visual group was also significantly lower than the haptic group for false positives. Visual also had significantly less false negatives than the haptic group. The auditory and haptic groups were not significantly different for correct detections, false positives, or false negatives.

Table 9. Tukey contrasts for correct detections between modalities

	Std.	**SE**	**z**	**P>|z|**
Haptic – Auditory	-0.122	0.080	-1.525	0.279
Visual – Auditory	-0.054	0.078	0.699	0.764
Visual – Haptic	0.176	0.0.082	2.160	0.078

Table 10. Tukey contrasts for false positives between modalities

	Std.	**SE**	**z**	**P>|z|**
Haptic – Auditory	0.530	0.703	0.753	0.731
Visual – Auditory	-3.005	0.777	-3.866	<0.001*
Visual – Haptic	-3.534	0.782	-4.521	<0.001*

Table 11. Tukey contrasts for false negatives between modalities

	Std.	**SE**	**z**	**P>|z|**
Haptic – Auditory	0.805	0.442	1.822	0.162
Visual – Auditory	-0.842	0.512	-1.643	-1.643
Visual – Haptic	-1.647	0.498	-3.307	0.003*

For Tukey contrasts for the blocks (see Tables 12, 13, and 14), there were no significant differences in all pairwise comparisons between blocks for correct detections. There were significantly less false positives in blocks 2, 3, and 4 in each pairwise comparison to block 1. There were no other significant differences for false positives. Block 1 had significantly less false negatives than block 3. Block 1 also had significantly less false negatives than block 4. Block 2 had significantly less false negatives than block 3, and block 2 also had significantly less false negatives than block 4.

Table 12. Tukey contrasts for correct detections between blocks

	Std.	**SE**	**z**	**P>|z|**
Block 2 – Block 1	-0.021	0.086	-0.244	0.995
Block 3 – Block 1	-0.134	0.091	-1.469	0.456
Block 4 – Block 1	-0.124	0.090	-1.380	0.512
Block 3 – Block 2	-0.112	0.094	-1.200	0.626
Block 4 – Block 2	-0.103	0.093	-1.105	0.686
Block 4 – Block 3	0.009	0.096	0.098	1.000

Table 13. Tukey contrasts for false positives between blocks

	Std.	**SE**	**z**	**P>|z|**
Block 2 – Block 1	-1.809	0.311	-5.824	<0.001*
Block 3 – Block 1	-2.120	0.329	-6.444	<0.001*
Block 4 – Block 1	-2.147	0.327	-6.559	<0.001*
Block 3 – Block 2	-0.311	0.325	-0.956	0.775
Block 4 – Block 2	-0.338	0.324	-1.042	0.725
Block 4 – Block 3	-0.027	0.323	-0.083	1.000

Table 14. Tukey contrasts for false negatives between blocks

	Std.	**SE**	**z**	**P>|z|**
Block 2 – Block 1	0.348	0.370	0.940	0.778
Block 3 – Block 1	1.276	0.320	3.992	<0.001*
Block 4 – Block 1	1.204	0.323	3.731	0.001*
Block 3 – Block 2	0.928	0.296	3.249	0.006*
Block 4 – Block 2	0.856	0.289	2.965	0.015*
Block 4 – Block 3	-0.072	0.219	-0.330	0.987

Aim 2: Cognitive Load

For Aim 2, cognitive load was measured by reaction time in seconds from when the alarm stimulus appeared to when the participant pressed the spacebar on the keyboard. Reaction times were recorded only for correct detections. Therefore, there were a total of 896 reaction times analyzed in total.

Average Times

Table 15 shows the average times for each block and modality. The auditory group had higher averages for all blocks in comparison to the visual and haptic groups.

Table 15. Average reaction times (seconds)

Block	Visual	Auditory	Haptic
1	1.04	2.13	1.02
2	1.30	2.59	1.13
3	1.17	3.54	1.19
4	1.26	4.67	1.26

Mixed-Effects Model

After checking assumptions, outliers were removed, and a logarithmic transformation was performed to fix assumptions of normality and homoscedasticity. In the final mixed-effects linear regression model, the haptic modality was significantly faster than the auditory group. The visual modality was also significantly faster than the auditory group (shown in Table 16). Blocks 2, 3, and 4 each took significantly longer compared to block 1 (shown in Table 16).

Table 16. Mixed-effects model for times

	β	**SE**	**t**	**P>|t|**
(Intercept)	0.870	0.101	8.622	<0.001*
Haptic	-0.948	0.135	-6.993	<0.001*
Visual	-1.049	0.136	-7.733	<0.001*
Block 2	0.156	0.035	4.413	<0.001*
Block 3	0.308	0.036	8.474	<0.001*
Block 4	0.466	0.040	11.753	<0.001*

Tukey Contrasts

Looking at the post-hoc Tukey HSD contrasts, the auditory modality was significantly greater in reaction time than the haptic group. Also, the auditory group had significantly greater reaction times than the visual group (shown in Table 17).

Table 17. Tukey contrasts for reaction times between modalities

	Std.	**SE**	**z**	**P>|z|**
Haptic – Auditory	-0.948	0.136	-6.993	<0.001*
Visual – Auditory	-1.049	0.136	-7.733	<0.001*
Visual – Haptic	-0.101	0.132	-0.767	0.723

For post-hoc Tukey contrasts for blocks, all contrasts were significant. Overall, as the block number increased, so did the reaction time (shown in Table 18).

Table 18. Tukey contrasts for reaction times between blocks

	Std.	**SE**	**z**	**P>|z|**
Block 2 – Block 1	0.156	0.035	4.413	<0.001*
Block 3 – Block 1	0.308	0.036	8.474	<0.001*
Block 4 – Block 1	0.466	0.040	11.753	<0.001*
Block 3 – Block 2	0.153	0.036	4.224	<0.001*
Block 4 – Block 2	0.310	0.040	7.798	<0.001*
Block 4 – Block 3	0.157	0.040	3.907	<0.001*

Summary of Findings

Below is a summary of findings for correct detections, false positives, false negatives, and reaction times. The summary tables indicate the significant findings from the data analysis. The tables are read from row to column, green indicates an advantage (e.g., the "row" performs significantly better than the "column"), and red indicates a disadvantage (e.g., the "row" performs significantly worse than the "column"). A dash indicates that no significance was found between the row and column.

Correct Detections

Overall, there were no significances between the modalities or between the blocks in terms of correct detections (shown in Table 19 and Table 20).

Table 19. Summary of correct detections for modalities

	Visual	**Auditory**	**Haptic**
Visual	-	-	-
Auditory	-	-	-
Haptic	-	-	-

Table 20. Summary of correct detections for blocks

	Block 1	**Block 2**	**Block 3**	**Block 4**
Block 1	-	-	-	-
Block 2	-	-	-	-
Block 3	-	-	-	-
Block 4	-	-	-	-

False Positives

In terms of false positives, the visual modality had significantly less false positives than auditory and haptic individually; therefore, the visual modality has an advantage compared to auditory and haptic (shown in Table 21). Auditory is thus disadvantageous compared to visual and haptic is also disadvantageous compared to visual when looking at false positives. Also, blocks 2, 3, and 4 each had significantly less false positives than block 1 (shown in Table 22). Therefore, block 1 was significantly worse compared to block 2, 3, and 4, individually.

Table 21. Summary of false positives for modalities

	Visual	**Auditory**	**Haptic**
Visual	-		
Auditory		-	-
Haptic		-	-

Table 22. Summary of false positives for blocks

	Block 1	**Block 2**	**Block 3**	**Block 4**
Block 1	-			
Block 2		-	-	-
Block 3		-	-	-
Block 4		-	-	-

False Negatives

The visual modality had significantly less false negatives than haptic; therefore, visual has the advantage over haptic in terms of misses (see Table 23). There was not a significant difference between the haptic modality and the auditory modality, nor was there a significant difference between the visual modality and the auditory modality. Blocks 1 and 2 had significantly less false negatives than block 3 (shown in Table 24). Blocks 1 and 2 also had significantly less false negatives in comparison to block 4. Therefore, blocks 1 and 2 had the advantage over blocks 3 and 4 in terms of fewer misses.

Table 23. Summary of false negatives for modalities

	Visual	**Auditory**	**Haptic**
Visual	-	-	
Auditory	-	-	-
Haptic		-	-

Table 24. Summary of false negatives for blocks

	Block 1	**Block 2**	**Block 3**	**Block 4**
Block 1	-	-		
Block 2	-	-		
Block 3			-	-
Block 4			-	-

Reaction times

The visual group had significantly shorter reaction times compared auditory; therefore, visual has an advantage over auditory in terms of cognitive load (see Table 25). Additionally, the haptic group had significantly shorter reaction times compared to auditory; therefore, haptic is preferred over auditory in terms of a reduced cognitive load. Blocks 2, 3, and 4 all had significantly longer reaction times than block 1 (shown in Table 26). Blocks 3 and 4 had significantly longer reaction times than block 2. Block 4 had significantly longer reaction times than block 3. Therefore, the analysis shows how reaction times increase as the study progresses.

Table 25. Summary of reaction times for modalities

	Visual	**Auditory**	**Haptic**
Visual	-		-
Auditory		-	
Haptic	-		-

Table 26. Summary of reaction times for blocks

	Block 1	**Block 2**	**Block 3**	**Block 4**
Block 1	-			
Block 2		-		
Block 3			-	
Block 4				-

CHAPTER V

CONCLUSION

There are many auditory and visual alarms in hospitals, and there is typically an overabundance of false alarms. The use of only two modalities over a long period of time can lead to information overload and alarm fatigue. A touchless haptic alarm interface could aid in mitigating alarm fatigue by offloading to a new modality and freeing up other cognitive resources. It can also create a redundancy gain to help clinicians in responding to alarms. The objective of this study was to investigate a haptic touchless alarm system by comparing it to a visual and auditory alarm system in a continuous monitoring vigilance task. The aims of this research were to study the effect of alarm modality on monitoring performance and cognitive load. Cognitive load was measured in terms of reaction times, and performance was measured in terms of correct detection, false positives, and false negatives.

Correct detections, false positives, and false negatives are indicators of performance. High performance would be minimizing false positives and false negatives while also having a high correct detection rate. If there are many false positives or many false negatives, this indicates low performance. After modeling a univariate mixed-effects negative binomial model, correct detections did not have any significance between the modalities or blocks. Therefore, no modality group performed better than the other group in correctly reacting to the alarm stimuli.

This shows that regardless of the modality used or the time of the monitoring task, the number of correct detections remained consistent.

The visual modality group was significantly better than the auditory group and significantly better than the haptic group as there were less false positives. This shows that if the auditory or haptic modalities are used, there may be a risk of more false alarms reacted to in the environment, which can lead to alarm fatigue. There were no differences between the haptic and auditory displays for false positives; therefore, the haptic and auditory modalities had a similar performance in terms of false positives. Block 1 showed significantly more false alarms than any other blocks. This may reflect a learning curve of the experiment as there was no practice session. Many participants may have doubted themselves in the first block when waiting for the arrival of the first alarm stimulus which led to them reacting to more non-alarm stimuli.

For false negatives, the visual group was significantly better than the haptic group. This shows that if haptic displays are used, there may be a risk of having more false negatives than when using a visual display. The visual modality and the auditory modality were not significantly different in terms of false negatives. Block 1 had significantly lower false negatives than block 3 and significantly lower false negatives than block 4. Block 2 also had significantly lower false negatives than block 3 and significantly lower false negatives than block 4. Therefore, if any modality is used for alarm monitoring, it should be known that the number of false negatives may increase as the monitoring task is performed for a prolonged period of time. This decrease in performance shows the effect of the vigilance decrement.

Cognitive load was measured with reaction time in seconds. A longer reaction time can be an indicator of a higher cognitive load (Horsky et al., 2003). Reaction times showed that the visual group was significantly shorter than the auditory group, and thus may have a lower cognitive load compared to auditory. Furthermore, the haptic group was also significantly lower than the auditory group suggesting that the haptic modality has a lower cognitive load compared to an auditory modality. All block contrasts were significant; therefore, reaction time increased as block number increased. This promotes the idea that cognitive load increases with time in all modalities. This supports the "mindfulness" stance and a high cognitive workload for monitoring tasks.

Overall, the results suggest that the visual modality performs the best comparatively for performance and reaction times. There were no differences in correct detections; therefore, all modalities may perform well for detecting alarms. However, auditory and haptic modality groups performed poorly in terms of false positives when compared to visual alarms. The haptic group also performed poorly in terms of false negatives when compared to visual alarms. However, haptic alarms had a significantly lower cognitive load compared to auditory alarms; therefore, haptic alarms may be a better fit than auditory alarms for reducing overall cognitive load.

The visual modality performing the best is consistent with industry as visual alarms are heavily prevalent in healthcare systems. However, auditory alarms are prevalent in almost every area of patient care and can sound thousands of times a shift (Deb & Claudio, 2015; Mitka, 2013; Roche et al., 2021). These alarms can be overwhelming due to their noise level and overabundance (Lewandowska et al., 2020). Visual alarms are useful in creating a redundancy gain with the auditory alarms but require focus on a screen to process information. Auditory alarms can be perceived from anywhere within a spatial limit of the soundwaves. The user does not have to focus on one area to perceive an auditory alarm; thus, they are omnidirectional. In this study, the auditory group performed worse in terms of cognitive load and performed worse than the visual modality in false positives.

Touchless haptic interfaces have many advantages. Firstly, they can be used by the user without physical contact with the surfaces (Brown et al., 2022). In healthcare settings bacteria spread is an issue that can be reduced by reducing the number of surfaces that are contacted. Therefore, integrating a new touchless alarm system will not increase bacteria spread (Paneva, Seinfeld, Kraiczi, & Müller, 2020). Unlike wearable tactile devices, they are unintrusive to the user (Paneva et al., 2020). In this study, the haptic alarm interface showed to have a lower cognitive load and was not significantly different in terms of correct detections for alarms, so it may be a promising modality to continue to study for healthcare systems to mitigate alarm fatigue. This is a novel input and output modality that is still being developed; however, results show that it could be promising to study for healthcare alarm monitoring. By offloading to another modality, vigilance decrement and therefore alarm fatigue can be mitigated under the foundation of the multiple resource theory. The haptic modality shows promise in that the modality group performed as well or better than at least one of the other modalities.

Another main finding of this work is demonstrating the difficulty of analyzing vigilance data in human factors research. The data for the counts of correct detections, false positives, and false negatives are considered multivariate because of the multiple outputs. It is also considered longitudinal because the 4 blocks are in a continuous time order. The analysis then requires a multivariate mixed-effects model; however, this cannot be done because these models do not converge, thus a frequentist statistical approach will not work. Frequentist models are used more frequently in the human factors area than Bayesian models. The flagship journal, Human Factors, only has three papers published total on Bayesian approaches (Alambeigi & McDonald, 2023; DinparastDjadid et al., 2021; Neyens, Boyle, & Schultheis, 2015).

There are several disadvantages to using a frequentist approach. Frequentist approaches are dependent on many assumptions that can be challenging to meet when looking at data collected from human subjects as people can vary greatly in their behavior. Frequentist approaches require “frequency” or the idea that an experiment must be repeated multiple times until a certain point (i.e., until significance is observed). Based on the number of experiments, it is determined if we reject or accept the hypothesis with the evidence that we have. Depending on when the experiment was stopped, there could be large differences in the results as it could affect point estimates and p-values. Bayesian statistical approaches are completely different compared to frequentist approaches both in terms of data structure and theoretical foundation. The Bayesian model utilizes prior beliefs based on probabilities, thus prior data can be incorporated into the analysis. The belief is updated and changed as more data is collected by calculating the posterior distribution. The posterior distribution is used to make interpretations from the model. Bayesian approaches work well with human factors experiments because participants develop new beliefs about a computer system state when interacting with a computer system with prolonged use. In this study, participants gained new beliefs as the study increased over time. They initially may have had a learning curve with the experiment, but then experienced a vigilance decrement that affected how they interacted in the system. They also may adapt and change their response bias to either be more liberal (i.e., say "yes" there is an alarm more often than "no") or conservative (i.e., say "no" there is not an alarm more often than "yes"). The Bayesian model would be able to model this information with posterior distributions as new data is being collected. Future work should explore a complete data analysis with the vigilance data from this experiment from a Bayesian perspective.

Limitations and Future Work

The data for the counts of correct detections, false positives, and false negatives are multivariate and longitudinal, and needs a Bayesian analysis rather than a frequentist approach. This study was limited to using three univariate mixed-effects models to analyze the data. Since a multivariate approach was not used, there may be an inflated alpha in the results meaning there could be false alarms in the findings. However, an inflated alpha value would ensure that there is a low number of missed findings, and a low number of missed findings is preferred for initial studies so that they can better inform how to design hypotheses for future studies. A Bayesian analysis would allow for a better interpretation of the data but is difficult to model and outside the scope of this thesis.

The participants were students recruited from Oklahoma State University and may be a limitation to this study. The results could differ depending on the age groups using the modalities. A more diverse sample and including participants from different areas could be beneficial. Also, including healthcare professionals who may have experience with responding to alarms would be beneficial to understanding the monitoring task. Another limitation is the lack of a practice session. A practice session was not included as this could have affected the vigilance decrement; however, by not including the practice session, participants may have had a learning curve that resulted in more false positives in block 1. Furthermore, cognitive load was measured in terms of reaction times and although an increase in reaction times indicate an increase in cognitive load, future work should investigate other methodologies for collecting data on workload, such as physiological measures. Lastly, the touchless haptic display is currently only available in an experimental format. Therefore, as a commercial version becomes available, further research should be done in terms of touchless haptic display development.

Future research should additionally investigate the use of a touchless haptic system as an alarm interface in healthcare applications and other industries, such as aviation. Studying the use of the haptic system along with the visual and auditory modalities could be the next step in understanding if it would help with a redundancy gain and mitigating alarm fatigue. Also, another area of study would be designing a touchless haptic system so that it can be integrated into a healthcare setting as an alarm. This is a new input and output modality that needs to continue to be researched to understand how it could be integrated without being invasive to the end user. Integrating a touchless haptic system can be a challenge in that it has never been studied as a person is moving throughout a space. It is important that the haptic system remains touchless so that there is no risk of surface contamination. In terms of alarms, future work could investigate redundant alarm systems when adding haptic as a redundancy gain to either visual or auditory alarm systems.

Impacts and Implications

Novel interfaces such as touchless haptic interfaces can be a new tool in the research toward solving alarm fatigue. By implementing a new modality, we can offload information from the prominent and overabundant auditory and visual alarms that are in the healthcare system. By offloading information to a new modality, we can reduce the cognitive load that occurs when performing vigilance tasks. Alarm monitoring is a vigilance task, especially for clinicians as they work long shifts. Also, touchless haptic interfaces allow the user to receive information without having to risk the spread of bacteria onto surfaces or wearing invasive devices. Alarm fatigue is a patient safety issue, so implementing new technology to reduce its effects is essential. Because the touchless haptic group performed similar to the groups with a visual or auditory interface, it can be a new avenue of research. Touchless haptic interfaces are still new and have many challenges when looking at practical implementation, but future research can work on implementation as a next step.

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APPENDICES

APPENDIX A. IRB APPROVAL FORM

Oklahoma State University Institutional Review Board

Date:	03/03/2023
Application Number:	IRB-23-99
Proposal Title:	Evaluation of Touchless Haptic Displays for Alarm Monitoring: A Comparison Study Between Auditory, Visual, and Haptic Interfaces
Principal Investigator:	Katie Jurewicz
Co-Investigator(s):	
Faculty Adviser:	
Project Coordinator:	
Research Assistant(s):	Ainsley Kyle, Jimmy Uba, Kylie Dowers, Matthew Nare
Processed as:	Exempt
Exempt Category:	

Status Recommended by Reviewer(s): Approved

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in 45CFR46.

This study meets criteria in the Revised Common Rule, as well as, one or more of the circumstances for which continuing review is not required. As Principal Investigator of this research, you will be required to submit a status report to the IRB triennially.

The final versions of any recruitment, consent and assent documents bearing the IRB approval stamp are available for download from IRBManager. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be approved by the IRB. Protocol modifications requiring approval may include changes to the title, PI, adviser, other research personnel, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms.
2. Submit a request for continuation if the study extends beyond the approval period. This continuation must receive IRB review and approval before the research can continue.
3. Report any unanticipated and/or adverse events to the IRB Office promptly.
4. Notify the IRB office when your research project is complete or when you are no longer affiliated with Oklahoma State University.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact the IRB Office at 405-744-3377 or irb@okstate.edu.

Sincerely,
Oklahoma State University IRB

VITA

Kylie Hope Dowers

Candidate for the Degree of

Master of Science

Thesis: INVESTIGATING VIGILANCE FOR AUDITORY, VISUAL, AND HAPTIC INTERFACES IN ALARM MONITORING

Major Field: Industrial Engineering and Management

Biographical:

Education:

Completed the requirements for the Master of Science in Industrial Engineering and Management at Oklahoma State University, Stillwater, Oklahoma in May, 2023.

Completed the requirements for the Bachelor of Science in Industrial Engineering and Management at Oklahoma State University, Stillwater, Oklahoma in 2022.

Experience:

Graduate research assistant in the Human-Systems Engineering and Applied Statistics (HSEAS) Lab at Oklahoma State University, Stillwater, Oklahoma.

Fabrication Intern at Spirit AeroSystems in Wichita, Kansas from May 2022 to August 2022.

Manufacturing Intern at Niagara Bottling in Oklahoma City, Oklahoma from May 2021 to July 2021

Professional Memberships:

Alpha Pi Mu, Human Factors and Ergonomics Society, Institute of Industrial and Systems Engineers, Tau Beta Pi