AMERICAN UNIVERSITY OF BEIRUT

# EYE TRACKING STUDY ON VIGILANCE DECREMENTS IN CLOSED CIRCUIT TELEVISION MONITORS

by
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# AN EYE TRACKING STUDY ON VIGILANCE DECREMENTS IN CLOSED CIRCUIT TELEVISION MONITORS

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# ABSTRACT
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Vigilance is the ability to sustain attention for a certain period of time. Vigilance decrements occur when a person is unable to maintain vigilance on a given task and performance suffers as a result. Vigilance decrements are common in long and monotonous tasks, such as Closed Circuit Television (CCTV) surveillance and can have detrimental consequences on the efficiency and safety of the system. There is thus a need to detect and inform users about these decrements. However, this requires analyzing eye tracking metrics over a shorter and earlier window of time than in previous studies. The overall goal of this study was to determine the attentional costs of vigilance decrements over a relatively short window of time. The application domain was CCTV surveillance. To this end, eighteen students from the American University of Beirut monitored a CCTV screen with four video feeds for suspicious events, such as taking the belongings of others. Performance measures were used to establish the presence of performance decrements. Eye tracking metrics were collected in two-minute intervals throughout the experiment as well as in two larger intervals. In general, the results revealed a trend of participants' attention becoming faster and more spread out, as evidenced by shorter mean fixation duration and longer mean saccade length. The results can be used as the basis for further research on vigilance and eye tracking metrics over short windows of time, which can, in turn, help inform the design of adaptive displays that help prevent vigilance decrements.

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# CHAPTER I

# INTRODUCTION

One of the major ironies of automation in the workplace is that human roles are reduced to only monitoring the system, but at the same time they should be aware of any breakdowns so that they can be ready to intervene if needed (Bainbridge, 1983). Continuous monitoring of a system would then require an operator to maintain constant vigilance. Vigilance is defined as the ability to maintain attention and detect stimuli over extended periods of time (Warm et al., 2008). Examples of complex domains in which vigilance plays an important role include electrocardiogram monitoring in medical environments (Martin-Gill et al., 2007), video surveillance involved in the oil and gas industries (Johnsen & Stene, 2014), traffic monitoring (Li et al., 2019), and closed-circuit television (CCTV) monitoring (Donald, 2001).

However, maintaining vigilance over extended periods of time is challenging given that vigilance tasks are tiring (Wickens et al., 2008), monotonous (Bodala et al., 2016), stressful (Szalma & Hancock, 2006), and accompanied by high mental workload (Temple et al., 2000). The resulting loss of vigilance is what has been termed *vigilance decrements*, as evidenced by a decline in stimuli detection performance over time (Al-Shargie et al., 2019; Davies & Parasuraman, 1982). The time frame for vigilance decrements could range from them occurring after 5 minutes in high workload conditions (Temple et al., 2000)  to after 2 hours (Tickner & Poulton, 1975). Regardless of the how soon they occur, vigilance decrements in complex systems can have catastrophic consequences, such as nuclear meltdowns (Reinerman-Jones et al., 2016) or medical complications (Scott et al., 2006).

There is thus a need to be able to predict and detect vigilance decrements in real time to prevent significant performance breakdowns. This would require the use of some objective, real time measure of vigilance. Eye tracking is one tool that can be used in this regard, as it has been successfully used in the past to monitor vigilance decrements (e.g., (Bergasa et al., 2006; Bodala et al., 2016; McIntire et al., 2014)

However, the work that has been done so far in this regard has mainly looked at vigilance decrements over relatively long periods of time during the vigilance task (e.g., 10 minutes in McIntire et al. (2014) and long after performance has deteriorated.

## A. Goal and Specific Aims

The overall goal of this study was thus to determine the attentional costs of vigilance decrements over a relatively short window of time. Being able to detect vigilance decrements in this way would then make it possible to trigger real-time display adjustments before major performance breakdowns occur. The focus is on CCTV surveillance, as it is a monitoring task that is well-known to involve vigilance decrements over time (Donald, 2001; Howard et al., 2009). To this end, the specific aims of this research are to:

1. Use performance measures to find the cutoff point between vigilant and non-vigilant states.

2. Determine how attention allocation – by means of eye tracking metrics – is affected by vigilance decrements.

# CHAPTER II

# BACKGROUND

## A. Vigilance Decrements

Vigilance decrements have largely been interpreted in the literature in light of one of three theories: resource theory (Helton & Warm, 2008), mindlessness theory (Manly et al., 1999), or resource control theory (Thomson et al., 2015). Resource theory refers to the availability of motivation and mental resources to perform demanding tasks (Davies & Parasuraman, 1982). According to resource theory, vigilance decrements are due to the depletion of resources as task time and demand increase (Neigel et al., 2019). On the other hand, according to the mindlessness theory, repetitive tasks with increased monotony require more attentional control to provide the correct response, and this becomes harder as time increases (Gartenberg et al., 2018). And finally, resource control theory merges both theories. It states that executive control decreases as task time increases, resulting with vigilance decrements; accordingly, this occurs because both attentional resources are limited overall and executive control is essential to combat the absorption of attentional resources by mind wandering (Thomson et al., 2015). Some of the factors that affect vigilance decrements in general are summarized in Table 1.

*Table 1 Factors Affecting Vigilance Decrements*

| | Effect | References |
|---|---|---|
| Number of feeds | Detection performance decreases as number of cameras increase | (Tickner & Poulton, 1973) |
| Task Engagement | Increased task engagement results in less vigilance decrements | (Neigel et al., 2019) |
| Event rate | Lower event rates results in better performance | (Claypoole et al., 2019) |
| Experience (work exposure) | Vigilance is maintained for longer durations with experience | (Donald, 2019) |
| Caffeine Consumption | Caffeine consumption improves performance | (Temple et al., 2000) |
| Signal Salience | Performance in vigilance tasks increases as salience increases | (Temple et al., 2000) |

## B. CCTVs and Vigilance Decrements

CCTV operators are required to monitor screens for long periods of time to detect and respond to critical events that could occur within seconds (Donald et al., 2015). CCTV surveillance can be boring, frustrating, and tedious (Donald et al., 2015). According to the resource theory, operators are thus required to remain motivated across the entire time period to maintain acceptable performance. There are many factors that affect vigilance in CCTV operations. For example, the nature of the monitored images and the number of video feeds being monitored simultaneously are likely to induce fatigue, reduce attentional resources, and increase cognitive workload of CCTV operators (Donald, 2019).

With regards to the time at which vigilance decrements occur in CCTV tasks, the finding are mixed. Many experiments have indicated a drop in performance after 20 to 35 minutes from the start of the vigilance task (e.g., (Ellis, 1970)). In one case, a two-hour CCTV task resulted in vigilance decrements but not a 1-hour task (Tickner & Poulton, 1973). On the other hand, more recent studies have reported that vigilance decrements occurred much earlier. In some vigilance task of monitoring rapid presentations of numerals in a heavy workload environment of around 60 events/minute, vigilance decrements occurred as early as in the first 5 minutes (Nuechterlein et al., 1983), and after 10 minutes of monitoring repetitive presentation of letters (Temple et al., 2000). For other normal conditions, vigilance decrements have also occurred after 10 minutes of monitoring repetitive presentation of letters (Temple et al., 2000), and after 30 minutes in a task of monitoring for the appearance of shapes inside boxes, with a 15% reduction in detection performance (Pattyn et al., 2008). According to (Teichner, 1974), vigilance decrements occur within the first 15 minutes of watch under many conditions.

## C. Measuring Vigilance Decrements

Several approaches have been used to measure vigilance decrements. Common ways o analyze performance measures include response time (Körber et al., 2015; Pattyn et al., 2008), correct detection rates (Szalma & Hancock, 2006; Temple et al., 2000) and false alarms (Sawin & Scerbo, 1995). Subjective measures, such as NASA Task Load Index (TLX) have also been used to measure the perceived mental workload that accompanies vigilance decrements (Claypoole et al., 2019, Warm, 1996 #60). NASA-TLX consists of a set of scales that measure physical demand, frustration, performance, mental demand, temporal demand, and effort, where lower scores indicate lower mental workload. Other neuroimaging measures have also been used to assess the decrease in the brain activity during vigilance decrements. Examples of such techniques are functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and transcranial Doppler (TCD) sonography (Donald et al., 2015). Others employed physiological techniques include electroencephalography (EEG) (Bodala et al., 2016) and eye tracking (Gartenberg et al., 2018; Moacdieh & Sarter, 2012), the focus of this study.

## D. Eye Tracking Basics

An eye tracker is a tool that uses infrared light to track where a person is looking at in a display (Cooke, 2005). Eye trackers track eye movements by sending out near infrared light towards the pupil, causing reflections that are translated by the eye tracker as points of regard (Poole & Ball, 2006). Eye tracking is used extensively as a tool to study eye movements in various research fields, from medical diagnostic and psychological research to gaze-controlled interactive applications and usability studies (Majaranta & Bulling, 2014). The rationale behind the use of eye tracking is the eye-mind hypothesis, which states that where a person is looking is the same as where a person's attention is (Just & Carpenter, 1980).

Furthermore, there are many benefits to using eye tracking in human factors research.

Compared to other physiological tools, such as electrocardiogram (ECG) and electroencephalogram (EEG), eye tracking is noninvasive (Shojaeizadeh et al., 2019). Eye tracking data can also be obtained in real time (Majaranta & Bulling, 2014), meaning that eye tracking can be used to trigger real-time display adjustments as in (Atrey et al., 2008).

Nevertheless, eye tracking does have some limitations. Although in most cognitive ergonomics and human factors research, eye movements have provided great opportunities of understanding of various aspects of cognition (Poole & Ball, 2006), the eye-mind hypothesis may not always hold. Other challenges, such as the sensitivity of eye trackers to changes in the levels of light, are continuously being improve (Majaranta & Bulling, 2014).

The building blocks of eye tracking are fixations and saccades. Fixations, during which visual processing occurs (Findlay, 2004), are defined as pauses typically between 200 and 600ms (Majaranta & Bulling, 2014). Saccades are eye movements between fixations (Majaranta & Bulling, 2014), that take about 30 to 120 ms each and are measured by quick jumps of two degrees or longer (Jacob, 1995). The sequence of saccades and fixations is called the scanpath (Poole & Ball, 2006).

Fixations and saccades can then be used to calculate a wide range of different metrics that can provide further insight into attention allocation. In general, eye tracking metrics can be divided into spread, directness, and duration metrics (Moacdieh & Sarter, 2015). Spread metrics are related to the location and dispersion of fixations across a display. Directness metrics, on the other hand, provide information on the sequence of fixations and how efficiently a person is navigating the display. Finally, duration metrics are related to the duration of fixations, or how long a person is looking at a particular area.

Eye tracking metrics have shown to estimate vigilance decrements in various environments. For example, eye blink duration and frequency were correlated with detection performance to estimate levels of vigilance (McIntire et al., 2013). A decrease in the number of fixations on targets and in the average length of each fixation occurred right before a miss (Gartenberg et al., 2018). Additionally, saccade amplitude decreases while eye blink frequency and duration increase with vigilance decrements (Bodala et al., 2016). However, to the best of my knowledge, there is limited research regarding the eye tracking metrics that best measure vigilance decrements occurring during surveillance task. Specifically, research emphasis is lacking on the use of eye tracking to study vigilance decrements moment-by- moment to identify the vigilant state from non-vigilant. Based on the information provided by the directness and duration of fixations, it is essential to determine which of these metrics best indicate the decline in performance. Indeed, there should be some generic metrics, defined without any specific areas of interest that reflect vigilance decrements in CCTV operators. Not only there is a need to determine metrics that best reflect vigilance decrements in a large window, metrics that reflect vigilance decrements in a short window, just before and just after the start of vigilance decrements, are to be determined in order to allow real time detection of these decrements.

# CHAPTER III

# METHODS

## A. Participants

The study was first approved by the American University of Beirut (AUB) Institutional Review Board. Eighteen students from AUB above the age of eighteen participated in the experiment. The data of two participants was disregarded for one participant misunderstood the instructions and the eye tracking data of the other participant was not collected by the software. All had normal or corrected to normal vision. No previous experience in CCTV monitoring was needed. Information regarding gender, age, major, year, caffeine consumption, and amount of sleep was collected from participants for control.

## B. Location and Setup

Experiments took place at the Ergonomics Lab (Scientific Research Building, Room (407) at AUB. Participants were seated in front of a 24 inch desktop screen with a 1920x1200 pixels resolution. A Tobii X3-120 eye tracker, an infrared, non-invasive eye tracker, was fixed on the screen. This eye tracker was used to track eye movements of participants. Participants were situated at a distance of 50 to 60 cm from the monitor. The experimenter used a second monitor to track the eye tracking output in real time.

## C. Stimuli and Tasks

The experiment procedure consisted of monitoring simulated CCTV video feeds. Four video feeds (V1 to V4) were displayed on the screen, given that operators can simultaneously monitor four camera feeds effectively (Atrey et al., 2008). Participants were asked to monitor these four video feeds for suspicious events. The videos used were taped specifically for this study and filmed on campus at the Oxy Irani Engineering Complex Graduate Lounge. There, four students were taped four times while studying, resulting in four videos of 30 minutes each, as vigilance tasks often last 30 minutes to hours (Davies & Parasuraman, 1982), (see Figure 1). There were two types of events that the four student actors were asked to simulate: target events (that participants have to detect) and distractor events. A target event is a “suspicious act” that the experiment participants would need to detect. The actors were asked to take the belongings of other students, or items that were placed near other students. On the other hand, a distractor event is a non-suspicious event, such as students reaching out to their own possessions and using them, getting closer to each other, laughing and talking, moving around the room, etc. No reaction to these distracting events was required on the part of the experiment participants. Distractor events were fully randomized where participants were asked to behave normally throughout the entire time. The rate of target events was one every 2 minutes, resulting in a total of 15 target events throughout the 30 minutes. The choice of the target event rate was based on pilot testing where levels of boredom and task difficulty were measured through a debriefing questionnaire. The interval between target events was randomized so that participants do not start expecting the target event, yet the inter-stimulus interval was between 1 and 3 minutes. The videos were muted and presented in black and white, similar to real CCTV video feeds. Moreover, the locations of the videos on the screen were fully counterbalanced across participants.

*Figure 1 CCTV Screen*

## D. Experiment Design

*Independent Variables.* The independent variable in this experiment is the presence vigilance decrements (present, absent). The presence of vigilance decrements was induced by watching a 30-minute video. Vigilance decrements were assumed to occur when performance metrics decline. Performance metrics were collected from the beginning of the vigilance task in intervals of two minutes to find the cutoff point between these two phases.

*Dependent Variables.* Performance, eye tracking, and subjective metrics were collected. The performance metrics which included the response time, target misses, and false alarms were collected in two-minute non-overlapping intervals. Each two-minute time frame represented a window as shown in Table 2. Response time is the time between the occurrence of the target event and the user's detection of the target event. Target misses are the missed target events, and false alarms are the falsely assumed target events. The eye tracking metrics of Table 2 were calculated over the whole vigilance decrements and no-vigilance decrements phases in two minute intervals as early as the task starts. The average eye tracking metrics during the entire vigilance and non-vigilant phases are also calculated. The subjective measures were measured through debriefing questionnaire. The debriefing questionnaire, administered at the end of the experiment, collected information regarding how they felt regarding the changes in performance during of the experiment, rating of the task difficulty, and the ability of maintaining the same attention level throughout the task.

*Table 2 Dividing Time Frames into Windows*

| Minutes (from – to) | 00-02 | 02-04 | 04-06 | 06-08 | 08-10 | 10-12 | 12-14 | 14-16 | 16-18 | 18-20 | 20-22 | 22-24 | 24-26 | 26-28 | 28-30 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Window | W1 | W2 | W3 | W4 | W5 | W6 | W7 | W8 | W9 | W10 | W11 | W12 | W13 | W14 | W15 |

*Table 3 Eye Tracking Metrics*

| Metric | Explanation | Justification |
|---|---|---|
| Mean Saccade Length (pixels) (Moacdieh & Sarter, 2012) | Average of the length of saccades | A longer saccade is an indicator of a less efficient scan (Coral, 2016) |

| | | |
|---|---|---|
| Mean fixation duration (seconds) (Moacdieh & Sarter, 2012) | Mean duration of all fixations within a defined period | A longer fixation duration is an indicator of difficulty in information extraction (Just & Carpenter, 1976) |

## E. Experiment Procedure

Participants were asked to read and sign the consent form. After that, participants went through a training session, and were introduced to their role, the target events and distracting events, and all the experiment instructions. Next, participants did a 4-minute training session on a mock video. They had to complete this training task successfully to be able to continue the experiment. Then the eye tracker was calibrated and the experiment session started. After the 30 minutes of monitoring were completed, participants were asked to fill the debriefing questionnaire. The total duration of the experiment was around one hour.

# CHAPTER IV

# RESULTS

The significance level was set at 0.05 for all analyses, which was done using IBM SPSS Statistics software. The assumption of normality was held for all metrics ($p > 0.05$). The cutoff point for vigilance decrements was considered to be Window 9, which is after 16 minutes (based on the results of (Teichner, 1974) that vigilance decrements occur after 15 minutes from the start of the task). Moreover, windows compared to Window 1 started with Window 6, as the literature shows that vigilance decrements in normal conditions occur after more than 10 minutes have passed (Ellis, 1970; Pattyn et al., 2008; Warm et al., 2008). Moreover, the analysis of the response time data showed that Window 10 is an outlier, as the average of Window 10 was found to be greater than Q3+1.5*IQR, where Q3 is the third quartile and IQR is the interquartile range. The reason behind this could be that this event was less salient and harder to detect compared to the events in other windows, and as a result, this window's target event was missed by approximately 63% of the participants. Window 10 was thus removed from the analysis.

## A. Performance Metrics

### 1. *Response Time*

Response time was calculated for all target event hits. The windows after Window 5 were compared to Window 1 (i.e., when there are no vigilance decrements) in intervals of 2 minutes using a paired t-test. The response time results of all windows are represented in Figure 2. The paired t-test results in Table 4 showed that there were 9 windows with significant difference in response time.

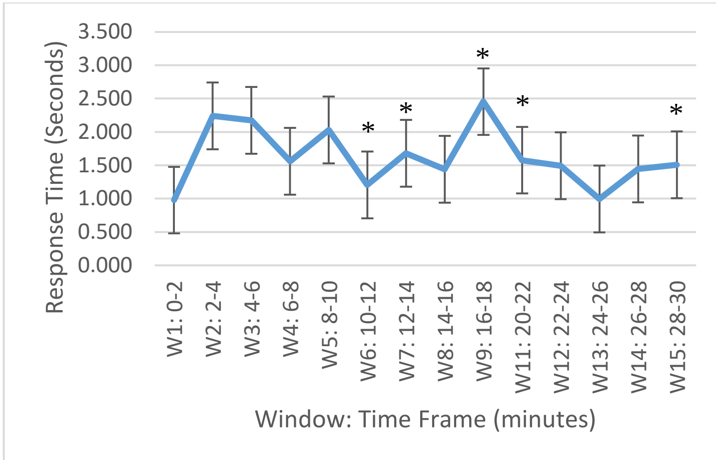


*Figure 2 Average response time plot*

Cohen's d was then used to measure of effect size and the largest effect size was found for Window 9, with ($M$ = -1.350, $SD$ = 1.225) and $p < 0.001$, where the mean (standard error of the mean) increased from 0.978 (0.124) seconds to 2.454 (0.202) seconds.

*Table 4 Paired t-test results of response time in Windows 6 to 15 compared to Window 1*

| Window compared to Window 1 | *Mean (SD)* | *Std. Error Mean* | *Paired Differences95% CI of the DifferenceLower* | *Paired Differences 95% CI of Difference Upper* | *t* | *df* | *p*-value | *Cohen's d* |
|---|---|---|---|---|---|---|---|---|
| W6 | -0.309 (.471)* | 0.29 | -0.61 | -0.01 | -2.50 | 9 | .044 | .727 |
| W7 | -0.737 (.932)* | 0.31 | -1.40 | -0.07 | -1.51 | 15 | .03 | 1.104 |
| W8 | -0.462 (1.225) | 0.27 | -1.11 | 0.19 | -5.03 | 11 | .15 | |
| W9 | -1.350 (.930)* | 0.50 | -1.94 | -0.76 | -7.32 | 5 | .0004 | 2.202 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| W11 | -0.601 (.851)* | 0.31 | -4.94 | -2.37 | -1.40 | 9 | .016 | 0.828 |
| W12 | -0.432 (.978) | 0.16 | -1.13 | 0.27 | -.34 | 10 | .19 | |
| W13 | -0.55 (.534) | 0.23 | -0.41 | 0.30 | -1.93 | 14 | .73 | |
| W14 | -0.447 (.897) | 0.19 | -0.94 | 0.05 | -3.11 | 14 | .07 | |
| W15 | -0.579 (.721)* | 0.29 | -0.98 | -0.18 | -2.50 | 9 | .0076 | 0.981 |

A paired-t-test compared average response time before Window 9 (pre cutoff) to the average response time after Window 9 (post cutoff). The result showed no significant increase in the average response time (see Figure 3).

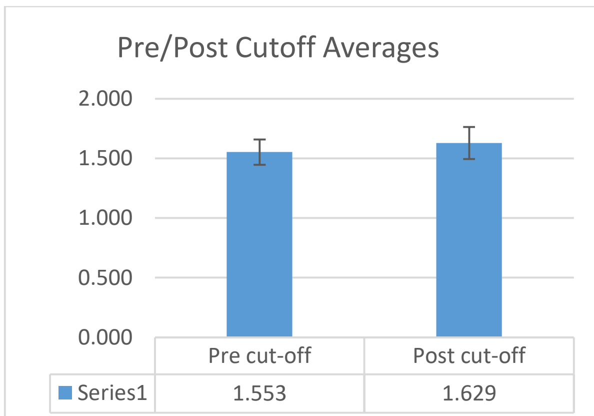


*Figure 3 Pre/post cutoff response time averages*

*Table 5 Pre/post cutoff paired t-test*

| Pre/post Averages | *Mean (SD)* | *Std. Error Mean* | *Paired Differences 95% CI of the Difference Lower* | *Paired Differences 95% CI of Difference Upper* | *t* | *df* | *p*-value |
|---|---|---|---|---|---|---|---|
| Response Time | -0.041(.523) | 0.13 | -0.320 | 0.238 | -0.311 | 15 | 0.760 |

## 2. ***Misses***

The number of participants who missed the event in each window is shown in Figure 4. A paired t-test compared all windows to Window 1. The results show significant increases in misses by participants per window in Windows 12, and 13. The result of the paired t-test of the other windows are represented in Table 6.

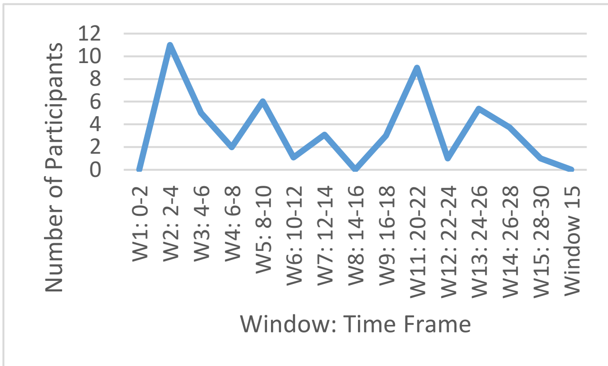


*Figure 4 Number of participants who missed the target event in each window*

*Table 6 Paired t-test results of event misses* in *Windows 6 to 15 compared to Window 1*

| Window compared to Window 1 | *Mean (SD)* | *Std. Error Mean* | *Paired Differences95% CI of the Difference of the Difference Lower* | *Paired Differences95% CI of Difference Upper* | *t* | *df* | *p-value* |
|---|---|---|---|---|---|---|---|
| W6 | -.125 (.342) | 0.07 | -0.23 | 0.08 | -1 | 13 | 0.336 |
| W7 | -.250 (.447) | 0.11 | -0.46 | 0.03 | -1.88 | 13 | 0.082 |
| W8 | | | | | | | |
| W9 | -.188 (.403) | 0.07 | -0.21 | 0.08 | -1 | 14 | 0.334 |
| W11 | -.0625 (.250) | 0.13 | -0.64 | -0.11 | -3 | 15 | 0.009 |
| W12 | -.375 (.500)* | 0.12 | -0.52 | -0.01 | -2.26 | 14 | 0.041 |
| W13 | -.313 (.479)* | 0.06 | -0.2 | 0.07 | -1 | 15 | 0.333 |
| W14 | -.0625 (.250) | 0.07 | -0.21 | 0.08 | -1 | 14 | 0.334 |
| W15 | - | - | - | - | - | - | - |

### 3. *False Alarms*

The number of falsely assumed events in each window is represented is Figure 5. The paired t-test was also used to compare all windows starting from Window 6 to Window 15 to Window 1; however, no window showed significant difference (see Table 7)

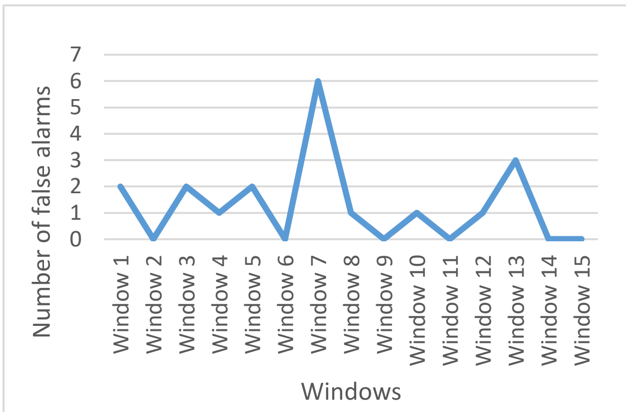


*Figure 5 False alarms in each window*

*Table 7 Paired t-test results of false alarms in Windows 6 to 15 compared to Window 1*

| Window compared to Window 1 | *Mean (SD)* | *Std. Error Mean* | *Paired Differences 95% CI of the Difference Lower* | *Paired Differences 95% CI of Difference Upper* | *t* | *df* | *p*-value |
|---|---|---|---|---|---|---|---|
| W6 | 0.143 (0.363) | 0.1 | -0.07 | 0.35 | 1.47 | 13 | 0.17 |
| W7 | -0.286 (0.611) | 0.16 | -0.64 | 0.07 | -1.75 | 13 | 0.10 |
| W8 | 0.071 (0.475) | 0.13 | -0.20 | 0.35 | 0.56 | 13 | 0.58 |
| W9 | 0.143 (0.363) | 0.1 | -0.07 | 0.35 | 1.47 | 13 | 0.17 |
| W11 | 0.071 (0.267) | 0.07 | -0.08 | 0.23 | 1 | 13 | 0.34 |
| W12 | 0.143 (0.363) | 0.1 | -0.07 | 0.35 | 1.47 | 13 | 0.16 |
| W13 | 0.071 (0.267) | 0.07 | -0.08 | 0.23 | 1 | 13 | 0.34 |
| W14 | -0.071 (0.475) | 0.13 | -0.35 | 0.20 | -0.56 | 13 | 0.58 |
| W15 | 0.143 (0.363) | 0.10 | -0.07 | 0.35 | 1.47 | 13 | 0.17 |

## B. Eye tracking Metrics

The eye tracking metrics of Windows 6 to 15 were also compared to window 1. Eye tracking metrics were collected over 2-minutes intervals from the beginning of the task.

### *1. Mean Fixation Duration*

The result of the mean fixation duration calculation can be seen in Figure 6. There was a significant difference in the mean fixation duration in Window 9 ($M$ = 14.980, $SD$ = 26.049) and $p$ = .036 and Window 15 ($M$ = -139.262, $SD$ = 77.134) and $p < .01$. Table 8 summarizes the results of the Paired t-test for all windows.

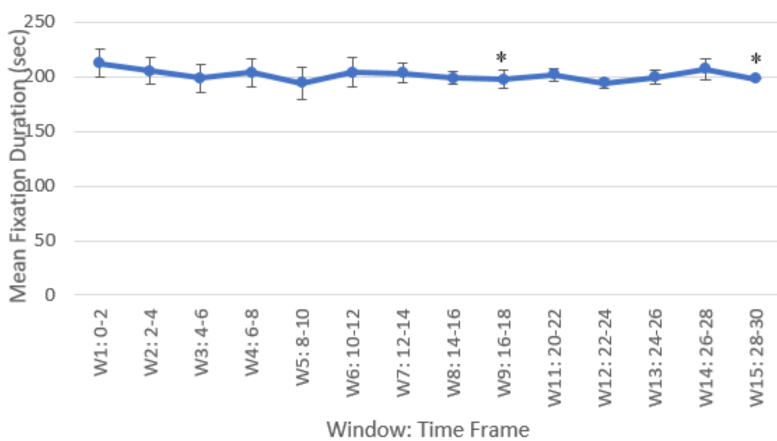


*Figure 6 Mean fixation duration time series*

*Table 8 Paired t-test results of mean fixation duration in Windows 6 to 15 compared to Window 1*

| Window compared to Window 1 | *Mean (SD)* | *Standard Error of the mean* | *Paired Differences 95% CI of the Difference Lower* | *Paired Differences 95% CI of Difference Upper* | *t* | *df* | *p*-value |
|---|---|---|---|---|---|---|---|
| W6 | 10.806 (20.337) | 5.44 | -0.94 | 22.92 | 1.89 | 13 | 0.068 |
| W7 | 10.598 (19.395) | 5.6 | -1.73 | 26.98 | 2.09 | 11 | 0.085 |
| W8 | 13.343 (25.601) | 6.4 | -0.3 | 28.86 | 2.3 | 15 | 0.055 |
| W9 | 14.98(26.049)* | 6.51 | 1.1 | 30.24 | 1.82 | 15 | 0.036 |
| W11 | 13.897 (29.519) | 7.62 | -2.45 | 28.59 | 1.39 | 14 | 0.090 |
| W12 | 11.236 (31.334) | 8.09 | -6.12 | 24.91 | 0.6 | 14 | 0.19 |
| W13 | 5.462 (36.489) | 9.12 | -13.98 | 35.84 | 1.86 | 15 | 0.56 |
| W14 | 16.662 (34.626) | 8.94 | -2.51 | -98.16 | 7.22 | 14 | 0.083 |
| W15 | -139.262(77.134)* | 19.28 | -180.36 | 22.92 | 0.86 | 15 | 0.000 |

The pre and post cutoff averages were calculated for mean fixation duration. The results are summarized in Figure 7. However, the paired t-test comparing pre and post cutoff averages conducted on the mean fixation duration results did not yield significant differences. The results are represented in Table 9.

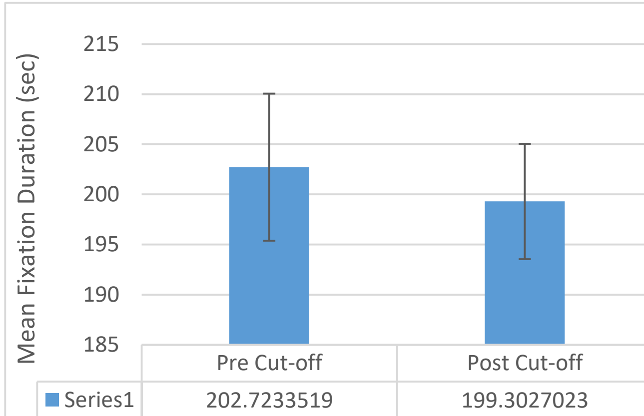


*Figure 7 Pre/post cutoff averages of mean fixation duration*

*Table 9 Paired t-test results of the pre-post cutoff averages of the mean fixation duration*

| Pre-post Cutoff | *Mean (SD)* | *Std. Error Mean* | *95% CI of the Difference Lower* | *95% CI of the Difference Upper* | *t* | *df* | *p-* value |
|---|---|---|---|---|---|---|---|
| Mean Fixation Duration | 4.161 (18.122) | 4.49 | -5.72 | 13.43 | 0.858 | 15 | 0.37 |

### ***2. Mean Saccade Length***

Mean saccade length for each window is represented in Figure 8. A paired t-test comparing mean saccade length of windows after Window 5 to Window 1 resulted with significant difference in Window 7 as well as the last 5 windows (i.e. windows 11 till window 15). Table 10 summarizes the mean saccade length paired t-test results.

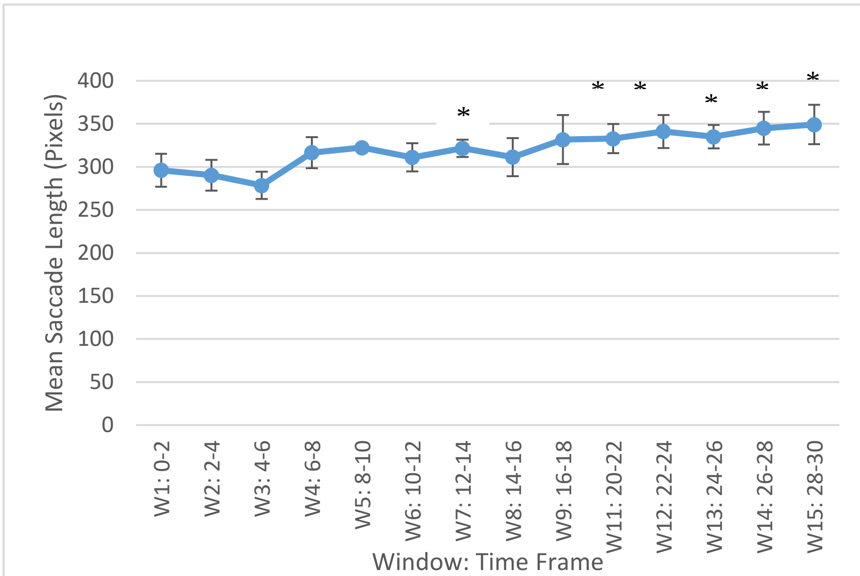


*Figure 8 Mean saccade length time series*

*Table 10 Paired t-test results of mean saccade length in Windows 6 to 15 compared to Window 1*

| Window compared to Window 1 | *Mean (SD)* | *Standard Error of the mean* | *Paired Differences 95% CI of the Difference Lower* | *Paired Differences 95% CI of Difference Upper* | *t* | *df* | *p*-value |
|---|---|---|---|---|---|---|---|
| W6 | -17.333 (42.292) | 11.30 | -53.57 | 9.54 | -1.42 | 11 | .18 |
| W7 | -28.401 (37.471)* | 12.71 | -40.23 | -3.23 | -2.514 | 10 | .031 |
| W8 | -12.967 (49.226) | 17.08 | -64.43 | 14.29 | -1.02 | 14 | .325 |
| W9 | -27.517 (63.926) | 11.78 | -58.98 | 9.39 | -1.611 | 13 | .131 |
| W11 | -33.705 (45.638)* | 13.34 | -71.96 | -8.43 | -2.86 | 14 | .013 |
| W12 | -43.352 (51.668)* | 13.73 | -59.36 | -14.74 | -3.25 | 14 | .006 |
| W13 | -29.706 (51.367)* | 15.42 | -75.69 | -0.05 | -2.164 | 13 | .050 |
| W14 | -41.752 (53.421)* | 18.68 | -97.49 | -7.81 | -2.707 | 11 | .020 |
| W15 | -57.121 (69.911)* | 9.32 | -49.82 | -16.76 | -3.057 | 13 | .009 |

The pre and post cutoff averages were calculated for the eye tracking metrics measured. The results are summarized in Figure 9. The paired t-test comparing pre and post cutoff averages conducted on the eye tracking metrics yielded significant differences with (M = -29.948, SD = 37.296) and $p < 0.001$ (see Table 11).

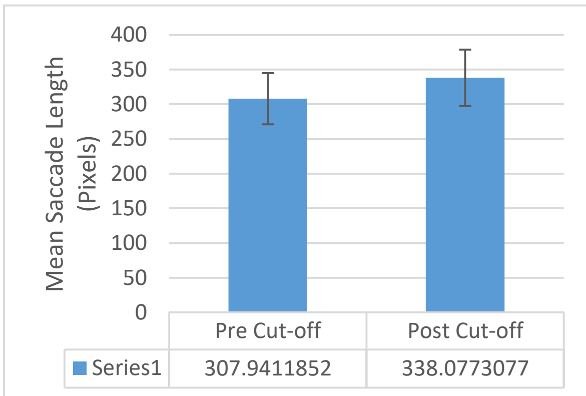


*Figure 9 Pre/post cutoff averages of mean saccade length*

*Table 11 Paired t-test results of the pre-post cutoff averages of mean saccade length*

| Pre-post Cutoff | *Mean (SD)* | *Std. Error Mean* | *95% CI of the Difference Lower* | *95% CI of the Difference Upper* | *t* | *df* | *p*-value |
|---|---|---|---|---|---|---|---|
| Mean Saccade Length | -29.948 (37.296) | 9.32 | -49.82 | -10.074 | 2 | 15 | 0.006 |

## C. Subjective Measures

*Debriefing questionnaire.* The results of the debriefing questionnaire regarding the change in detection performance are represented in Figure 11a. Those with worse performance mentioned that they lost attention with time, after a little time, and after 10 minutes. They also mentioned that they got bored, tired, zoned out, and found it hard to maintain the same level of concentration. The task difficulty results as perceived by participants are also presented in Figure 11b. Pie chart in Figure 11c represents the percentage of participants who reported they could not maintain the same level of performance and this who could not. Those who reported maintaining same level of attention mentioned that they forced themselves to stay focused by searching for major events and shifting to the different screens.

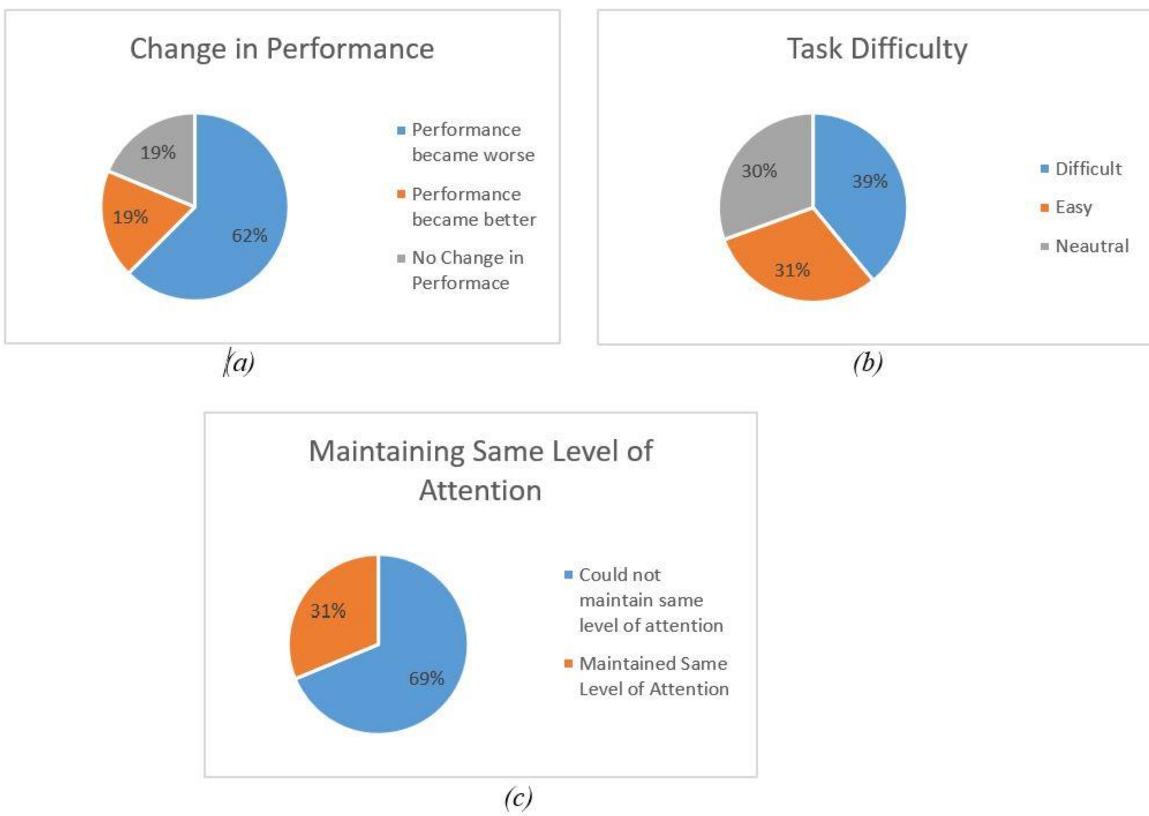


*Figure 10 Subjective Measures: (a) Change in performance, (b) Task difficulty, and (c) Maintaining same level of performance*

# CHAPTER V

# DISCUSSION

In this experiment, two objectives were investigated. The first objective was to use the performance metrics to find the cutoff point between the vigilant and the non-vigilant phases, which is after 16 minutes from the start of the task. And the second objective was to determine how attention allocation – by means of eye tracking metrics – is affected by vigilance decrements.

For the first objective, it seems that the setup used in this study did not elicit performance decrements as was seen in other studies where with time, response time to target events becomes progressively slower (Gartenberg et al., 2018; Luna et al., 2018). There was a significant increase in response time in Window 9, for example, with that window also having the largest effect size, but the vigilance decrements did not consistently continue beyond that. The same effects were seen for other performance measures.  It could be that the tasks participants were asked to do here were not consistent enough to be able to see performance decrements, or that the tasks themselves were too easy. Although (Temple et al., 2000) mentions rebound in performance towards the end of the task, the setup would have to be changed in order to do further analyses on this topic. All of this is despite the fact that participants felt that they lost vigilance and that the task was hard; it would seem that participants were misguided in this case.

However, this did not prevent looking at the second objective in order to get an idea of how eye tracking metrics change over time during a vigilance task. Only mean saccade length had significant increase in the pre- and post- cutoff. In general, there was an overall trend of mean fixation duration decreasing and mean saccade length increasing. Taken together, these metrics indicate that participants were quickly moving from one focus to another, and that these areas became farther apart. The reason behind this could be that participants felt they had to move faster between the four feeds to detect the event. Compared to other studies on vigilance decrements, saccade amplitude decreased (Bodala et al., 2016), and average fixation length increased right before a missed event (Gartenberg et al., 2018). In other studies on adopting these eye tracking metrics, mean fixation duration increased with performance decrements, and shorter saccades associated the decline in performance (Moacdieh & Sarter, 2017; Moacdieh & Sarter, 2012). This research study can serve as a starting point for further research on vigilance decrements. In particular, there were a number of limitations that plagued this study that would need to be adjusted. In specific, the tasks would have to be more controlled, the videos could be more realistic, and the sample size has to be larger (it was constrained here by the COVID pandemic). Moreover, developing models such as adding more events per window would make it feasible to determine the individual cutoff point for each participant. Other directness metrics such as the backtrack rate indicating the change in direction, where a higher value reflects less efficiency (Moacdieh et al., 2020). Also, spread metrics indicating attention dispersion (Moacdieh et al., 2020) such as the convex hull area, which is the minimum convex containing fixation points and spatial density, which is the result of dividing the number grid cells with gaze points by the number of cells (Goldberg & Kotval, 1999). All of these would be needed in order to better observe vigilance decrements. Moreover, future research could start the comparisons from the first window rather than Window 6, and also compare consecutive windows to each other. Comparing multiple windows using ANOVA should also be used to check if the means of these windows are statistically significant. Only then would it be feasible to determine which eye tracking metrics reflect vigilance decrements just before and just after vigilance decrements and thus allow real time detection. This will, in turn, along with real time adjustments, will improve the efficiency and safety of complex and critical environments where missing a stimulus could be detrimental or even fatal. Results of this research could form the basis of an adaptive display that alerts notify users in case of vigilance decrements. Finally, this would then serve as a starting point for further generalization to match CCTV monitoring tasks with different number of feeds and different rates, types, and salience of events, or even similar tasks in different domains. Examples of domains where such models could be used include airports, manufacturing facilities, or air traffic control.

# APPENDIX

An Eye Tracking Study on Vigilance Decrements in Closed Circuit Television

Monitors

Nadine Marie Moacdieh (PI), Habiba Ajour (Co-I)

Debriefing Questionnaire

1. Did your detection performance change during the experiment?
    a. Yes.
    b. No
2. If yes:
    a. Did your performance get better or worse?
        i. Better. Why and When? ______________________________
        ii. Worse. Why and When? ______________________________
3. How would you rate the detection task difficulty?
    a. Extremely easy
    b. Easy
    c. Neutral
    d. Difficult
    e. Extremely difficult
4. Were you capable of maintaining the same level of attention throughout the entire monitoring time?

a. Yes. How?

b. No. Why?

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