Spring 2021

A systematic analysis of eye-tracking metrics for sleepiness

Debasis Roy

Department:

A SYSTEMATIC ANALYSIS OF EYE-TRACKING METRICS FOR SLEEPINESS

by

DEBASIS ROY

A THESIS

Presented to the Graduate Faculty of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN INFORMATION SCIENCE AND TECHNOLOGY

2021

Approved by:

Dr. Fiona Fui-Hoon Nah, Advisor
Dr. Keng Siau
Dr. Michael Gene Hilgers

ABSTRACT

Sleepiness or sleep deprivation is a serious hazard that can be life-threatening in carrying out certain tasks (e.g., when driving or executing attention-critical tasks). Eye movement can provide cues on sleepiness. Hence, eye-tracking metrics have the potential to detect sleepiness.

In this research, we used a systematic analysis approach to identify eye-tracking metrics for sleepiness. We used several databases to identify independent experimental studies that have used eye-tracking metrics to assess sleepiness. We identified 25 studies that included 674 participants where the participants' data were captured both in an alert state and in a sleep-deprived state. In the analysis, we found six main categories of eye-tracking metrics for sleepiness: fixation, gaze, smooth pursuit, saccade, blink, and pupil size.

Keywords: Sleep deprivation, Sleepiness, Eye-tracking, Blink, Saccade, Fixation, Gaze, Pupil size, Smooth pursuit

ACKNOWLEDGMENTS

I am wholeheartedly grateful to my mentor and advisor, Dr. Fiona Fui-Hoon Nah, for her sincere efforts in helping me during my M.S. studies. I would not have accomplished my research work without her continual supervision and guidance. I am indebted to her for her support at each stage of my M.S. program. She helped me throughout my research and provided me all the guidance and help required to complete my research.

I would like to thank my thesis committee members, Dr. Keng Siau and Dr. Michael Hilgers, for their support, feedback, suggestions, and knowledge sharing to enhance my research.

Further, I acknowledge the support, suggestions, and help I have received from Dr. Matthew Thimgan in the Biology department and Dr. Ting Shen in the Psychology department. I thank both of them for their time in assisting me with various aspects of this research, i.e., understanding the complexity underlying the concept of sleep and the statistical analysis used in this research.

I would like to express my gratitude to students in the Laboratory of Information Technology and Evaluation (LITE), especially to Cooper Broman, Alec Mcdaniel, and Kyle Johnson, for sharing their valuable knowledge about eye-tracking devices and other equipment in the LITE lab.

I should not forget to acknowledge the contribution of my parents and especially my wife who supported me all the way to the completion of my studies. Finally, I would love to express my gratitude to God for being with me.

TABLE OF CONTENTS

Page

ABSTRACT iii

ACKNOWLEDGMENTS iv

LIST OF ILLUSTRATIONS vii

LIST OF TABLES viii

SECTION

1. INTRODUCTION 1

2. LITERATURE REVIEW 4

2.1. EYE TRACKING METRICS 4

2.2. SUMMARY OF LITERATURE FINDINGS 7

2.3. POPULAR SCALES USED IN THE STUDIES 19

2.3.1. MSLT 20

2.3.2. MWT 20

2.3.3. SSS 20

2.3.4. KSS 21

2.3.5. ESS 21

2.3.6. VAS 21

2.3.7. ATS 22

2.4. PSYCHOLOGICAL EFFECTS OF SLEEP DEPRIVATION 22

3. METHODOLOGY 25

3.1. INCLUSION CRITERIA AND STUDY SELECTION 25

3.2. CODING OF STUDY INFORMATION 26

4. DATA ANALYSIS. 30

4.1. MEASUREMENT 30

4.2. RESULTS 31

4.2.1. Pooling Effect Sizes of the Studies 31

4.2.2. Pooling Effect Size of the Key Metrics 34

5. DISCUSSION. 37

5.1. FIXATION 37

5.2. GAZE 38

5.3. SMOOTH PURSUIT 38

5.4. SACCADE 39

5.5. BLINK 40

5.6. PUPIL SIZE 41

6. LIMITATIONS AND FUTURE RESEARCH. 42

7. CONCLUSION. 44

BIBLIOGRAPHY 46

VITA 55

LIST OF ILLUSTRATIONS

Figure Page

4.1. Paper inclusion process flow chart. 32

4.2. Forest plot of the studies. 34

4.3. Forest plot of the key metrics... 36

LIST OF TABLES

Table Page

2.1. Summary of key eye-tracking metrics 5

2.2. Summary of literature findings 11

3.1. Demographic and imaging information of the included papers 27

4.1. Random effect model of the studies 33

4.2. Pooling effect size of the key metrics 35

1. INTRODUCTION

Sleep deprivation affects our ability to respond to and perform well in tasks. It increases human errors, reaction time, and time to complete tasks (Doran et al., 2000; Lim et al., 2008; Pilcher et al., 1996) Sleep deprivation can also increase the risks to our health, well-being, and longevity (Caldwell et al., 2019). It can negatively affect performance in computer-based tasks and create hazards to safety, such as in traffic control tasks (Pilcher et al., 1996). Sleep deprivation can impact behavior in the following ways (Lim et al., 2008): (i) it slows down reaction time; (ii) it increases errors on omission and commission; (iii) it increases time to complete tasks; (iv) its effect on vigilant attention is sensitive to circadian and homeostatic drives. The circadian drive promotes wakefulness according to one's biological clock while the homeostatic drive to sleep is affected by the duration of wakefulness.

Staying focused on any kind of job is important for successful completion of the job or for completing the job well and on time. The ability to be focused or attentive in a job can be affected by fatigue or sleepiness. "Fatigue is the state of feeling very tired, weary or sleepy resulting from insufficient sleep, prolonged mental or physical work, or extended periods of stress or anxiety. Boring or repetitive tasks can intensify feelings of fatigue. Fatigue can be described as either acute or chronic" (Caldwell et al., 2019). Lack of sleep and repetitive work can cause cognitive fatigue (Caldwell et al., 2019). In this research study, we are focusing mainly on sleep deprivation and their measures using eye-tracking metrics.

Cognitive fatigue that is tied to sleep deprivation is well-established as a serious health hazard. Fatigue and sleepiness in modern society are personal and occupational risk factors. There is substantial evidence that excessive sleepiness in the workplace and on the highway is a serious safety hazard, and there is mounting evidence that insufficient sleep poses significant risks to health, wellbeing, and longevity (Caldwell et al., 2019). Sleep deprivation in healthy adults induces widespread neurophysiological and endocrine changes, characterized by impaired cognitive functioning, despite increased regional brain activity (Klumpers et al., 2015). Sleep loss can result in increased reaction time, decreased vigilance, increased perceptual and cognitive distortions, and reduced cognitive abilities (Krueger, 1989). In addition to the negative impacts of sleep loss and disrupted circadian rhythms, fatigue that degrades cognitive performance can result from participating in long boring tasks such as highway driving, equipment monitoring, and flying highly automated aircraft (Caldwell et al., 2019). Pilcher and Huffcutt (1996) have shown that both short- and long-term sleep deprivation can affect any kind of task performance. Sleepiness or sleep deprivation can create a serious hazard in any kind of task performance. Eye movement can provide cues on sleepiness and hence, eye-tracking metrics can be used to assess sleepiness.

Li et al. (2016) mentioned various metrics that can detect the difficulties of understanding reading materials. Rayner (1998) also used eye-tracking metrics to identify different cognitive demands on tasks. Schleicher et al. (2008) found that in any repetitive work, sleep warnings can be issued based on metrics of eye movement.

Impaired cognitive functioning due to sleepiness manifests in the form of a decrease in sustained attention and reduced vigilance. Therefore, sleepiness results in higher risks of accidents and critical errors during situations in which constant levels of attention are exigent. Researchers have been trying to find easy and effective methods to identify and quantify sleepiness in humans through different methods. In this study, we will identify eye-tracking metrics for sleepiness.

A device that can measure the attention state and proactively respond as appropriate, to the attention state, can have great value. It may also serve and influence ease of use and aid intuitive human-computer interactions. Some of these can be illustrated in the specific scenarios of drone flying or robot-assisted surgery. Consider a robot-assisted surgery, primarily instructed by a human surgeon in real-time. A human error due to sleepiness or fatigue while interacting with the robotic computer can have devastating consequences. Measuring human attention while interacting with a computing device can be helpful to prevent human input errors in human-computer interactions.

The objective of this study is to carry out a systematic analysis to identify the important eye-tracking metrics which can be used to track sleepiness or sleep deprivation. We tried to categorize different bifurcated metrics for ease of analysis and to identify the most useful ones. We also tried to capture the studies according to the task performance, the different scales used in different studies, the length of sleep deprivation, and our studies include both partial and total sleep deprivation studies.

The thesis is organized as follows. Section 2 covers the background and literature review. Section 3 describes the methodology. Section 4 provides the data analysis of the study. Section 5 presents the discussions. Section 6 provides the limitations and future research, and Section 7 presents the conclusion.

2. LITERATURE REVIEW

This section provides the details about the background and literature review. It contains discussions about different metrics, metrics used to capture sleepiness in different studies, scales used in various studies, and the psychological effects of sleep deprivation.

2.1. EYE TRACKING METRICS

Eye movement and pupil size provide informative measures of sleepiness (Caffier et al., 2003; Fransson et al., 2008; Zils et al., 2005). These movements and dilations can be recorded and analyzed in a naturalistic workplace environment to detect the sleepiness of workers who are carrying out attention-critical tasks such as air traffic control. Many parameters of eye activity are not under voluntary control because different parts of the brain system work together to control eye movement and pupil dilation. In turn, the functioning of the brain system is affected by sleep deprivation. Zils et al. (2005) discovered that saccadic velocity, especially peak saccadic velocity, can be a reliable measure of fatigue from sleep deprivation. They indicate that other parameters of eye movements could also be associated with sleepiness.

Biometric measurements of the movement and condition of the eyes are termed oculometries. The eyes of an individual who is awake can take only one of three states: blink, movement, or fixation. Researchers have utilized eye-tracking metrics to study cognitive processing (Bera et al., 2019; Goldberg & Kotval, 1999; Kretzer & Maedche, 2018; Rayner, 2009), cognitive states (Marshall, 2007), mental effort (Buettner et al., 2018; Marshall, 2007), and task performance (Buettner et al., 2018). Some of the key eye-tracking metrics are shown in Table 2.1.

Table 2.1. Summary of key eye-tracking metrics

Metric	Definition	Interpretation
Fixation Count	Total number of fixations on an object	Higher count indicates that the viewer is facing problems with search efficiency (Goldberg & Kotval, 1998; Kotval & Goldberg, 1998)
Fixation Duration	Total time of fixation on an object	Longer fixation may indicate that a participant faces difficulty extracting information from a display (Fitts et al, 1950; Goldberg & Kotval, 1998)
Gaze % on each Area of Interest	The proportion of time looking at a display element	Longer duration reflects the difficulty of information extraction and frequency reflecting the importance of that area of the display (Fitts et al, 1950)
Saccade	The rapid motion of the eye from one fixation to another	The degree of smoothness of eye movements (e.g., distinct jumps) indicates the conditions of individual viewers (i.e., the endpoint cannot be changed once the saccade is initiated)

Table 2.1. Summary of key eye-tracking metrics (cont.)

Metric	Definition	Interpretation
Smooth Pursuit	The eye movement when following a moving object	The smoother the movement, the more stable or awake are the brain and the eyes
Areas of Interests (AOI's)	An Area of Interest (AOI) indicates selected regions of a displayed stimulus	While not strictly a metric by itself, it defines the area by which other metrics are calculated
Blink Amplitude	Distance traveled by the eyelid	Blinks are not all the same, and the larger the blink, the higher its velocity. With drowsiness, blinks are relatively slower for the same amplitude.
Blink Duration	Duration from when the eyelid starts moving down until it is fully up again	Normal blink frequency is on the order of 9 to 13 per minute in the daytime, increasing to 20 to 30 per minute with sleep deprivation.
Heatmaps	Heatmaps are visualizations that show the general distribution of gaze points	Heatmaps are color-coded. The red color may indicate that the viewer is unable to concentrate and stare at the points for a long time.

Table 2.1. Summary of key eye-tracking metrics (cont.)

Metric	Definition	Interpretation
Scan-path	Trajectories (paths) of the eyes when scanning the visual field and viewing and analyzing any kind of visual information	A smoother path means the participant is awake and focused. An uneven path means the participant is unable to concentrate.
Pupil Diameter	Aperture in an optical system or human eye	The normal pupil size in adults varies from 2 to 4 mm in diameter in bright light to 4 to 8 mm in the dark. The deeper the sleepiness, the more the pupil constricts.

2.2. SUMMARY OF LITERATURE FINDINGS

Various studies using different eye metric measurements have been carried out to detect cognitive operations and states. Marshall’s (2007) study correlated eye movement with human cognitive states. In her study, she made video recordings of the eye at high speed (typically 60–250 Hz) and in real-time with the help of a camera device that was either located on a lightweight headband or set up on a computer monitor. This setup captured three pieces of information related to the eye; pupil-size, eye movements, and blinks. These eye metrics are then analyzed with mathematical and statistical models to differentiate between cognitive states. The cognitive state classification rates were compared to those measured by three separate EEG studies and she concluded that engaged cognitive state, distracted cognitive state, and fatigue can be differentiated using eye metrics. Bera et al. (2019) used eye-tracking to detect and measure the cognitive process of associating information from various Area of Interests (AOIs). The eye-tracking metrics reveal viewers' visual associations between elements of a diagram. This visual association can be interpreted as cognitive integration that contributes to the performance of the cognitive task of understanding the diagram. Gidlöf et al. (2013) in their study show that in a real-time environment, eye-tracking can reveal differences in decision-making vs searching behavior.

Yang et al. (2012) in their study found that frequent eye blinking and long eye closure are different for sleep-deprived subjects and non-sleep deprived subjects. Ghimire et al. (2015) recognized the entire face as a valid observation area because facial gestures such as yawning can give strong indications of the driver's drowsiness state, but the study limited itself to eye-tracking to avoid the higher computational complexity inherent in entire facial gesture detections. Horng et al. (2004) successfully created a system that carries out facial and eye location detection and predicts drowsiness by noting when eyes are closed. Detection at the stage of dozing is rather comparatively primitive but an alert at the very moment of eye closure from dozing can still be a very effective fatigue detection system that can alert the driver on time.

Different sleep deprivation studies have been carried out using eye-tracking technology. Bocca and Denise (2006) confirm in their study that saccadic eye movements can reliably detect alertness and visuospatial attention simultaneously. They could also tag specific brain regions that are affected by total sleep deprivation, confirming a neurophysiological basis for the phenomenon. Sleep-deprived fatigue also results in delayed pupil light reflex and a significant decrease in velocity of saccadic movement (Rowland et al., 2005). Another similar study by Zils et al. (2005) discovered that saccadic velocity, especially peak saccadic velocity, can be a reliable measure of fatigue arising from sleep deprivation.

Eye blinks and fatigue are directly correlated. Caffier et al. (2003) studied eye-blinking patterns under different states of fatigue and found that blinks under drowsiness or sleepiness are prolonged in terms of eyes' closing time, reopening time, duration of closed time, and frequency of long closure duration blinks. Another study by Häkkänen et al. (1999) observed eye blink duration, frequency, and speed control in drivers affected by mild Obstructive Sleep Apnea Syndrome (OSAS). Sleep apnea could lead to under-optimal body rest and hence, cause daytime drowsiness. Thus, it measured daytime drowsiness in terms of blink metrics. It identified blink duration and blink frequency as indicators of sleepiness.

Another area of interest, that is relatively less explored, is the cognitive performance after awakening after total sleep deprivation. A study by Ferrara et al. (2000) found saccadic velocity and smooth pursuit eye movement were less than ideal after awakening from total sleep deprivation. This finding led to an interesting recommendation that total sleep-deprived subjects should not undertake any complex or critical tasks that need high oculomotor control soon after awakening. Sleep-induced fatigue exhibits strong sleep inertia immediately after awakening. The study by Drummond et al. (2005) observed performance deterioration after 36 hours of total sleep deprivation. The authors also noted a compensating attentional recovery that may be triggered after a particularly poor performance that occurred after total sleep deprivation. A study by Anderson et al. (2010) identified factors leading to less-than-ideal performance in a Psychomotor Vigilance Test (PVT) that was due to sleep deprivation-induced performance lag. Various other factors such as visual inattention (eyes open) or other distractions can potentially lead to reduced performance and thus may be attributive factors other than sleep-deprivation-induced lapses.

Functional magnetic resonance imaging (fMRI) is also a key indicator of sleep-related studies. Chee et al. (2008) used fMRI as a potential measurement tool to identify and differentiate cognitive states related to attentional deficits and as a result, correlations between visual attention or processing and sleep deprivation were detected. Johns (1991) and others proposed self-administered questionnaires to self-report states of sleepiness.

There have been several studies to measure sleepiness, human fatigue, or cognitive states using eye-tracking and other bio-physical indicators. The purpose of this study is to review and identify current state-of-the-art knowledge and research status of eye-tracking for different cognitive states, especially concerning the state of sleepiness. Here, the research topic is related to several ideas such as cognition, cognitive state or process, oculometry, sleep deprivation, cognitive performance tests, and so on. We reviewed multiple publications on eye-tracking studies. A summary of the studies and the metrics reviewed are provided in Table 2.2.

Table 2.2. Summary of literature findings

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Ahlstrom et al. (2013)	Using eye movements and sleep-wake predictor to estimate sleepiness of drivers in a fit-for-duty test	Eye movement features and sleep-wake predictor model can be used to predict severe sleepiness	• Saccade curvature • The amplitude ratio of sinusoidal smooth pursuit
Barbato et al. (1995)	Sleep deprivation affects spontaneous eye blinks	Blink rate increases with sleep deprivation, which increases central dopamine activity	• Blink frequency
Bocca & Denise (2006)	Saccadic eye movement was used to assess the effect of sleep deprivation	Saccadic eye movements can be used to assess alertness, sleep deprivation, and visuospatial attention	• Saccadic accuracy • Saccadic latency

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Caffier et al. (2005)	Measurement of eye-blink parameters for sleepiness	Blinks can be used to assess drowsiness or sleepiness	• Blink duration • Blink re-opening time • Blink frequency • The proportion of long-closure duration blinks
Crevits et al. (2003)	Effect of sleep deprivation on saccades and eyelid blinking	Sleep deprivation affects blink rate but not saccade latency or the number of saccade errors	• Blink frequency
De Gennaro et al. (2000)	Dissociation between speed and accuracy in total sleep deprivation	Saccade latency increases, saccade peak velocity decreases, and smooth pursuit velocity gain decreases with sleep deprivation	• Saccade latency • Saccade peak velocity • Smooth pursuit velocity gain

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Ferrara et al. (2000)	Oculomotor performance after sleep deprivation	Saccade latency increases, saccade velocity decreases, and smooth pursuit velocity gain increases after sleep deprivation	• Saccade latency • Saccade velocity • Smooth pursuit velocity gain
Fransson et al. (2008)	Smooth pursuit and saccadic eye movements in restricted sleep deprivation	Sleep deprivation decreases smooth pursuit gain, smooth pursuit accuracy, and saccade velocity, and affects the ratio between saccade velocity and saccade amplitude	• Saccade velocity • Saccade amplitude • Smooth pursuit velocity gain • Smooth pursuit accuracy

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Franzen et al. (2009)	Pupillary reactivity on sleep-deprived adults	Sleep-deprived individuals have larger pupil diameters when viewing negative pictures, which suggests greater reactions to negative emotional information	• Pupil diameter
Häkkänen et al. (1999)	Detect sleepiness through blink duration	Sleepiness increases blink duration	• Blink duration
Heaton et al. (2014)	Sleep deprivation decreases attention and visual tracking	Gaze instability and reaction time deterioration are found in sleep-deprived individuals	• Gaze stability
Ingre et al. (2006)	Blinking, lane drifting, and KSS in sleep-deprived driving	Blink duration increases with sleep deprivation	• Blink duration

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Jin et al. (1991)	Eye movement variables to detect driver sleepiness	Blink frequency, gaze direction, fixation duration, and percent eye closure (PERCLOS) can detect driver sleepiness	• Blink frequency • Gaze direction • Fixation duration • Percent eye closure (PERCLOS)
Kurylyak et al. (2006)	Infrared camera-based system to evaluate sleepiness	Blink time interval is shorter when sleepy than alert	• Blink frequency
Marshall (2007)	Measurement of metrics to identify cognitive states of a sleep-deprived subject	Assessed different cognitive states using eye metrics and corroborated with EEG measurements, and identified metrics that differentiate cognitive states including sleepiness	• Blink frequency • Pupil size • Saccade rate • Divergence (distance between horizontal locations of both eyes)

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Miles et al. (1931)	Extreme sleepiness can be detected by eye movement and visual fixation	Saccadic eye movement was slower and wavering of fixations was observed with sleepiness	• Saccade velocity • Gaze stability
Porcu et al. (1998)	Nighttime sleepiness indicators	Saccadic performance and smooth pursuit are affected by sleepiness	• Saccade accuracy • Saccade latency • Rejected (“inappropriate”) saccades • Smooth pursuit (velocity gain and phase)
Rowland et al. (2005)	Responses of oculomotor during partial and total sleep deprivation	Sleep deprivation induces fatigue and results in delayed pupil light reflex and decreased saccadic velocity	• Saccadic velocity • Latency to pupil constriction

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Russo et al. (2003)	Oculomotor impairment during chronic partial sleep deprivation	Saccadic velocity decreases and latency to pupil constriction increases with sleep deprivation	• Saccadic velocity • Latency to pupil constriction
Schleicher et al. (2008)	Eye movement indicators of fatigue for issuing sleepiness warnings	With increasing time in repetitive work, eye movements changed and by capturing different metrics, sleepiness warnings can be issued	• Blink duration • Delay of eyelid reopening • Blink interval • Eyelid closure speed • Saccadic duration • Fixation duration

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Shiferaw et al. (2018)	Sleep-deprived drivers' behavior	Gaze behavior, blink rate, blink duration, fixation rate, and saccade amplitude are affected by sleep deprivation	• Stationary gaze entropy • Gaze transition entropy • Fixation rate • Blink frequency • Blink duration • Saccade amplitude
Tong et al. (2014)	Sleep deprivation and visual tracking synchronization	Acute sleep deprivation degrades visual tracking and prediction capability becomes less precise	• Saccade velocity • Anticipatory saccade amplitude • Gaze stability • Smooth pursuit velocity gain
Wilhelm et al. (1998)	Pupil size measurement of sleep deprivation	Pupillary behavior is affected by sleep deprivation and pupillary oscillations quantify sleepiness	• Pupil size

Table 2.2. Summary of literature findings (cont.)

Reference	Research Focus	Key Findings	Eye-tracking Metrics
Yang et al. (2012)	Eyelid tracking for fatigue detection from sleep deprivation	An eye-tracking system was developed to predict fatigue from facial and eyelid tracking of sleep-deprived and non-sleep deprived individuals	• Blink frequency • Percent [of] eye[lid] closure (PERCLOS)
Zils et al. (2005)	Differential effects of sleep deprivation on saccadic eye movements	Saccadic eye movements can detect sleep deprivation	• Saccadic peak velocity • Saccadic accuracy • Saccadic latency

2.3. POPULAR SCALES USED IN THE STUDIES

Sleepiness can impact performance in computer-based tasks. It can increase the response time, the number of errors made, and the time taken to complete a task (Lim et al., 2008). Popular scales that have been used to assess sleepiness include Multiple Sleep Latency Test (MSLT), Maintenance of Wakefulness Test (MWT), Stanford Sleepiness Scale (SSS), Epworth Sleepiness Scale (ESS), Karolinska Sleepiness Scale (KSS), Sleepiness Visual Analogue Scale (VAS), and Accumulated Time with Sleepiness (ATS). MSLT and MWT are laboratory-based methods to assess the ability to fall asleep and stay awake respectively. When focused attention is critical to a job that involves safety, MSLT and MWT can be used to assess the potential risk of work-related hazards or accidents. The SSS, ESS, KSS, VAS, and ATS are self-reported measures of sleepiness.

2.3.1. MSLT. MSLT is a validated measure of excessive daytime sleepiness that assesses the tendency to fall asleep (Littner et al., 2005). It is assumed that the sleepier a person is, the quicker he or she falls asleep. MSLT measures how fast a person falls asleep in a laboratory setup (i.e., in a dark and quiet controlled environment) with electrodes and wires attached so sleep can be monitored (Johns, 2000; Porcu et al., 1998). The testing for MSLT takes a full day as it involves assessments of sleep latency (i.e., the amount of time it takes to fall asleep) of five naps separated by two-hour breaks. Each nap lasts 15 minutes and each nap attempt will end after 20 minutes if sleep does not occur.

2.3.2. MWT. MWT is an assessment of the ability to stay awake for a defined duration (Littner et al., 2005). It assesses the wake tendency of a person while resisting falling asleep in a dull and quiet environment (Doghramji et al., 1997) MWT has been used to assess responses to interventions for disorders associated with excessive sleep. External factors such as light, temperature, and noise are isolated during the test.

2.3.3. SSS. SSS is a popular sleepiness scale that is widely used in sleep-related studies. SSS is a one-item self-reported assessment of sleepiness at a specific moment in time. Sleepiness is assessed on a scale of 1 to 7 (see https://web.stanford.edu/~dement/sss.html for the scale) to indicate the current level of sleepiness (Hoddes et al., 1972). SSS has also been used to assess mood change following a phase shift of the sleep-wake schedule (Maclean et al., 1992; Surridge-David et al., 1987).

2.3.4. KSS. Similar to SSS, KSS is also a one-item measure to assess sleepiness and has been validated against alpha and theta electroencephalographic (EEG) activity as well as slow eye movement electrooculographic (EOG) activity (Ahlstrom et al., 2013). It is rated on a 9-point scale (1 = extremely alert, 2 = very alert, 3 = alert, 4 = rather alert, 5 = neither alert nor sleepy, 6 = some signs of sleepiness, 7 = sleepy, but no effort to keep awake, 8 = sleepy, some effort to keep awake, 9 = very sleepy, great effort keeping awake, fighting sleep). It exists in two versions. The first version only labels the odd points in the scale (1, 3, 5, 7, 9) whereas the second version adds labels to the even points and hence, labels all 9 points in the scale (Miley et al., 2016).

2.3.5. ESS. ESS is a self-administered questionnaire of eight items to assess the general level of sleepiness (see https://epworthsleepinessscale.com/about-the-ess/ for the scale). It uses a 4-point (0-3) scale to assess the likelihood to doze off or fall asleep when engaged in eight different activities. The sum of the scores over the eight items or activities yields an overall score for average sleep propensity. The concept of ESS was derived from observations on the nature of the occurrence of daytime sleepiness (Johns, 1991).

2.3.6. VAS. VAS was developed to assess state or mood on a horizontal line with bipolar descriptions. It involves rating sleepiness along a line with both extremes labeled as ‘very sleepy’ and ‘very alert’ (Johnson et al., 1990; Monk et al., 1985). VAS can be used for rating a variety of states or moods that also include fatigue, tension, anger, vigor, sadness, and cheerfulness (McCormack et al., 1988; Sanchez et al., 2016).

2.3.7. ATS. ATS is an assessment of subjective sleepiness over long periods. It involves asking a person to estimate the proportion of wake times that he or she experiences symptoms of sleepiness such as heavy eyelids, irresistible sleepiness, and reduced performance (Waage et al., 2012). Ratings of ATS showed high correlations with those of KSS and VAS (Gillberg et al., 1994).

2.4. PSYCHOLOGICAL EFFECTS OF SLEEP DEPRIVATION

The need for sleep varies among individuals (Shneerson, 2000). The average sleep duration for a human body is around 7.5 to 8 hours (Kripke et al., 2002; Carskadon and Dement, 2005; Kronholm et al., 2006). Two processes of sleep regulations are circadian process C and homeostatic process S (Achermann, 2004). The theory on circadian process C posits the existence of control by an endogenous circadian pacemaker, which controls an onset and offset episode of sleep, whereas the homeostatic process S depends on wakefulness and the need for sleep; the need for sleep increases with wakefulness (Alhola et al., 2007). Sleep is important for several reasons such as body restitution, energy conservation, thermoregulation, and tissue recovery (Maquet, 2001). Good sleep is essential for cognitive performance and memory consolidation (Maquet, 2001; Stickgold, 2005). The lack of sleep can activate the sympathetic nervous system, which can lead to high blood pressure (Ogawa et al., 2003). Studies have shown that people who are sleep deprived usually experience a decrease in cognitive performance and a change of mood (Huffcutt, 1996; Philibert, 2005). Sleep loss or deprivation is one of the reasons for obesity and diabetes. Although obesity is itself a cause for diabetes in recent studies, it is found that sleep loss may increase glucose metabolism and increase the risk of diabetes independently. Sleep restriction that causes upregulation of appetite can be a reason for weight gain, which turn results in insulin resistance, a condition that increases the chance of diabetes (Knutson et al., 2007). Sleep deprivation deeply affects the ability of human beings to respond promptly to any task performance. Lim et al. (2008) stated that sleep deprivation broadly affects four areas of behavioral changes: 1. Sleep deprivation causes overall slowing of reaction times. 2. Sleep deprivation increases errors on omission and commission. 3. Sleep deprivation enhances the time on task effects. 4. The lack of vigilant attention due to sleep deprivation is sensitive to both circadian and homeostatic drives. Extended sleep deprivation influences competition for works according to the state-instability theory (Durmer et al., 2005). Though sleep loss affects individuals differently (Van Dongen et al., 2004), it is found that it increases the reaction time in a PVT task when a person is sleep-deprived (Doran et al., 2001; Pilcher et al., 1996; Edholm et al., 1965). Chronic restriction in sleep, i.e., 6 hours or less, causes cognitive performance deficits. It is also found that moderate sleep restriction could cause impaired waking neurobehavioral functions in healthy adults (Van Dongen et al., 2003; Drake et al., 2001). According to the study by Orzeł-Gryglewska (2010), sleep deprivation causes longer reaction time, distractedness, disturbances in attention and concentration, forgetting known facts, difficulty in memorizing new information, mistakes, and omissions.

Two vital cognitive domains in sleep deprivation are attention and working memory. Working memory is divided into four subparts: phonological loop, visuospatial sketchpad, the episodic buffer, and central executive (Baddeley and Hitch, 1974; Baddeley, 2000). The verbal and acoustic information is stored by the phonological loop;

visual information is stored by the visuospatial sketchpad; the episodic buffer gathers information from several different sources, and the central executive serves the overall control function (Alhola et al., 2007). Working memory plays a major role in certain attention functions (Baddeley et al., 1999), which is referred to as vigilance. Attention and working memory are both controlled by the frontal lobes of our brain (Naghavi and Nyberg, 2005). Since the frontal brain areas are vulnerable to sleep deprivation (Harrison et al., 2000; Thomas et al., 2000), we can conclude that both attention and working memory are compromised during prolonged wakefulness or if someone is sleep deprived.

3. METHODOLOGY

The data analysis was conducted through a systematic review of relevant studies (Moher et al., 2009). We searched the literature in the electronic databases of Scopus, IEEE, MEDLINE, PsycInfo, PubMed, and Scopus from their inception to December 2020. The keywords we used for the database search are consistent but the methodology used by the databases is slightly different. For Scopus & IEEE, we used “sleep deprivation” as a primary search term and within the list of results, we searched for “eye-tracking” and “eye tracking” to identify the relevant studies. For Medline, we used the query “("sleep deprivation"[All Fields]) AND (("eye-tracking"[All Fields] OR "eye-tracking technology"[All Fields] OR "eye tracking"[All Fields])”. In PsycInfo and PubMed, we used the keywords “sleep deprivation”, “eye-tracking” and “eye tracking” to identify the relevant studies. A total of 302 studies were found based on the above-mentioned search strategy; among them, 25 primary articles were relevant and hence, included in the systematic analysis, which is discussed in the next section.

3.1. INCLUSION CRITERIA AND STUDY SELECTION

We included studies where the participants were above the age of 19 and not having any significant medical or neurological conditions. We also checked if the participants in the studies have sleep-related issues such as sleep difficulties and if they were on any sleep-related medications in order to exclude them. Participants with a normal sleep cycle and a normal vision as well as no history of alcoholic abuse were included in the analysis.

For the study selection, we included studies where eye-tracking metrics were captured and data were captured in an alert state and the sleep-deprived state. Only experimental studies are included in the systematic analysis. There are two types of sleep deprivations: acute (24 hrs. or up of sleep deprivation) and partial (3-4 hrs. of sleep deprivation for a few nights) (Philip et al., 2012). Few studies we found are concerned with partial sleep deprivation (St-Onge et al., 2012; St-Onge et al., 2014; Poudel et al., 2013) and we excluded them from the analysis (Eickhoff et al., 2016).

Importantly, the included studies that are taken into consideration involved high sleep-deprived subjects (>20 hrs. of sleep deprivation). We found some experiments with overlapping samples and therefore, we included only one of them. Finally, after a close examination of these studies, we included 25 primary studies for the systematic analysis.

3.2. CODING OF STUDY INFORMATION

The final datasheet is created using the 25 final selected studies. A coding sheet was developed to capture the data from these studies. A total of 58 key metrics is captured from the studies involving 674 participants. Table 3.1 shows the demographic and imaging information of the included papers.

Table 3.1. Demographic and imaging information of the included papers

Sl. No	Reference	Eye-tracking Metrics	Metrics Category	No of Participants	Gender	Avg Age	Hr. of SD	Statistical Analysis type	Scale Used
1	Ahlstrom et al. (2013)	Saccade curvature	Saccade	24	M-12/F-12	35+/-9.6	24	between-studies	KSS
		Amplitude ratio of sinusoidal smooth pursuit	Smooth Pursuit						
2	Barbato et al. (1995)	Blink frequency	Blink	8	M-2/F-6	25+/-5	24	between-studies	
3	Bocca & Denise (2006)	Saccadic accuracy	Saccade	10	M-10	21	24	between-studies	ESS
		Saccadic latency	Saccade						
4	Caffier et al. (2005)	Blink duration	Blink	21	M-19/F-2	55.3	24	between-studies	ESS/VAS
		Blink re-opening time	Blink						
		Blink frequency	Blink						
		Proportion of long-closure duration blinks	Blink						
5	Crevits et al. (2003)	Blink frequency	Blink	21	M-10/F-11	25	20	between-studies	
6	De Gennaro et al. (2000)	Saccade latency	Saccade	5	M-5	29.67	24	between-studies	SSS
		Saccade peak velocity	Saccade						
		Smooth pursuit velocity gain	Smooth Pursuit						
7	Ferrara et al. (2000)	Saccade latency	Saccade	9	M-5	23.2	40	between-studies	VAS
		Saccade velocity	Saccade						
		Smooth pursuit velocity gain	Smooth Pursuit						
8	Fransson et al. (2008)	Saccade velocity	Saccade	18	M-10/F-8	23.8	36	between-studies	VAS

Table 3.1. Demographic and imaging information of the included papers (cont.)

		Saccade amplitude	Saccade						
		Smooth pursuit velocity gain	Smooth Pursuit						
		Smooth pursuit accuracy	Smooth Pursuit						
9	Franzen et al. (2009)	Pupil diameter	Pupil Size	30	M-15/F-15	24.4	24	between-studies	VAS
10	Häkkänen et al. (1999)	Blink duration	Blink	10	M-10		24	between-studies	MWT
11	Heaton et al. (2014)	Gaze stability	Gaze	87	M-68/F-19	21.8	26	between-studies	
12	Ingre et al. (2006)	Blink duration	Blink	10	M-5/F-5	37	24	within-studies	KSS
13	Jin et al. (1991)	Blink frequency	Blink	12	M-8/F-4	27.1	24	between-studies	KSS
		Gaze direction	Gaze						
		Fixation duration	Fixation						
		Percent eye closure (PERCLOS)	Blink						
14	Kurylyak et al. (2006)	Blink frequency	Blink	1	M-1		24	between-studies	
15	Marshall (2007)	Pupil size	Pupil Size	30	M-17/F-13	19.5	24	between-studies	
16	Miles et al. (1931)	Saccade velocity	Saccade	5	M-5		66	within-studies	
		Gaze stability	Gaze						
17	Porcu et al. (1998)	Saccade accuracy	Saccade	5	M-5	29.67	24	between-studies	MWT/MSLT
		Saccade latency	Saccade						
		Rejected (“inappropriate”) saccades	Saccade						
		Smooth pursuit (velocity gain and phase)	Smooth Pursuit						
18	Rowland et al. (2005)	Saccadic velocity	Saccade	12	M-12		64	between-studies	

Table 3.1. Demographic and imaging information of the included papers (cont.)

		Latency to pupil constriction	Pupil Size						
19	Russo et al. (2003)	Saccadic velocity	Saccade	66	M-50/F-16	35	26	between-studies	SLT/SSS
		Latency to pupil constriction	Pupil Size						
20	Schleicher et al. (2008)	Blink duration	Blink	138	M-76/F-62	33.4		between-studies	KSS
		Delay of eyelid reopening	Blink						
		Blink interval	Blink						
		Eyelid closure speed	Blink						
		Saccadic duration	Saccade						
		Fixation duration	Fixation						
21	Shiferaw et al. (2018)	Fixation rate	Fixation	9	M-4/F-5	33	24	between-studies	KSS
		Blink frequency	Blink						
		Blink duration	Blink						
		Saccade amplitude	Saccade						
22	Tong et al. (2014)	Saccade velocity	Saccade	87	M-68/F-19	21.8	26	between-studies	SSS
		Anticipatory saccade amplitude	Saccade						
		Gaze stability	Gaze						
		Smooth pursuit velocity gain	Smooth Pursuit						
23	Wilhelm et al. (1998)	Pupil size	Pupil Size	13	M-8/F-5	25	24	between-studies	SSS
24	Yang et al. (2012)	Blink frequency	Blink	28	M-14/F-14		24	between-studies	PVT
		(PERCLOS)	Blink						
25	Zils et al. (2005)	Saccadic latency	Saccade	15	M-15	23.7	24	between-studies	

4. DATA ANALYSIS

For the data analysis, we used the R language and R Studio. R studio is a powerful open-source and free platform for data analysis. R is specifically built for statistical analysis. It is widely used in various fields for data manipulation and data visualization. This data was created and stored as an RMD file written in R studio then converted into a word file by using Knit in R Studio which rendered the document. We created the RMD file by calculating and pooling the effect sizes in our coding sheet.

We used R for the meta-analysis because of its widely supported packages. Meta-analysis is a quantitative analysis of a dataset, created in the form of a systematic review and focused reviews.

4.1. MEASUREMENT

For assessment of the data, we used the “meta” package in R studio. Meta package is the most broadly used package for meta-analysis. For meta-regression to single-arm proportion calculation in a meta-analysis, the meta-package can be used. “metafor” package can be used to conduct a meta-analysis.

To conduct the meta-analysis, we prepared the data by calculating the effect size and standard error of effect size from the mean (M), standard deviation (SD), and sample size (N) we collected from the studies. Effect size tells us how a group is different from another. To calculate the effect size, we used the Hedge’s g method as it is recommended if the sample size is less than 20. We chose Hedges’ g over Cohen’s d because most of the sample sizes of studies included in our analysis are less than 20. In general, for a sample size greater than 20, both statistics are roughly equivalent.

We used the “metagen” function of “meta” package to pool the effect sizes. We used a forest plot for visualization of the data by using “forest” function.

4.2. RESULTS

Figure 4.1 depicts a flow chart that demonstrates how the included studies were obtained. These 25 studies include 58 eye-tracking metrics.

When pooling effect sizes, there are two methods: one is the Fixed-Effect Model and the other is the Random-Effects Model. Both of these methods need only the effect size and variance in each study for computations. These methods are also called generic inverse-variance methods. The fixed effect method assumes that all the studies are from a single homogeneous population. To calculate the overall effect, we averaged out all the effect sizes but give the studies with greater precision a higher weight. In the random effect model, the studies were not drawn from the same population and the study effect shows more variance than can be accounted for. As our study populations are quite different from one another, we found that the random effect models are quite suitable for this meta-analysis.

4.2.1. Pooling Effect Sizes of the Studies. When dealing with continuous outcome data, it is easy to calculate the Standardized Mean Difference (SMD) as an outcome for each study. A common format to calculate the SMD is Hedge’s g and to calculate the effect sizes, we used the Hedge’s g method. The formula for Hedge’s g is shown in Equation (1). Where (M1-M2) is the difference in mean and SD^*_{pooled} is the pooled and weighted standard deviation.

$$\text{Hedge's } g = (M1\text{-}M2)/SD^*_{pooled} \tag{1}$$

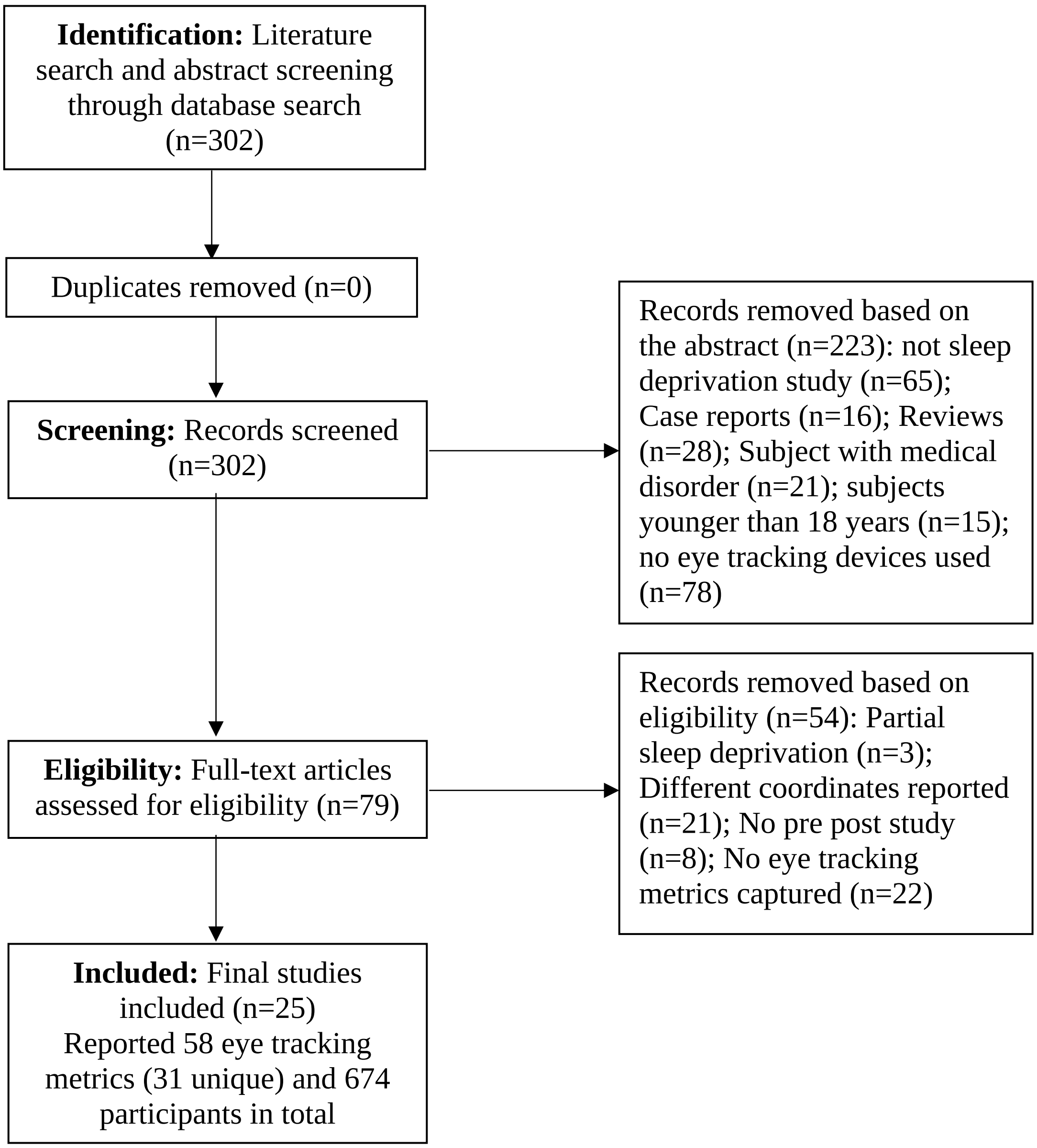

Figure 4.1. Paper inclusion process flow chart

Table 4.1. Random effect model of the studies

```
## Study                        SMD            95%-CI %W(random)
## Ahlstrom et al. (2013)   0.5659 [ 0.5519; 0.5799]        7.2
## Barbato et al. (1995)    1.0505 [-7.2650; 9.3659]        0.0
## Bocca & Denise (2006)    0.4386 [-1.3557; 2.2329]        0.5
## Caffier et al. (2005)    0.5697 [-0.2322; 1.3716]        2.1
## Crevits et al. (2003)    0.7186 [ 0.4619; 0.9752]        5.8
## De Gennaro et al. (2000) 0.0221 [-3.6389; 3.6830]        0.1
## Ferrara et al. (2000)    0.3966 [-0.4135; 1.2067]        2.1
## Fransson et al. (2008)   0.1526 [-0.0899; 0.3951]        5.9
## Franzen et al. (2009)    0.2222 [ 0.2218; 0.2225]        7.2
## HŠkkŠnen et al. (1999)   1.1225 [ 0.0069; 2.2382]        1.3
## Heaton et al. (2014)     0.8101 [ 0.7744; 0.8459]        7.2
## Ingre et al. (2006)      0.6565 [ 0.3590; 0.9540]        5.4
## Jin et al. (1991)        0.0413 [-0.0577; 0.1404]        7.0
## Kurylyak et al. (2006)   0.4990 [-1.4609; 2.4590]        0.5
## Marshall (2007)          0.9932 [ 0.9753; 1.0111]        7.2
## Miles et al. (1931)      0.0050 [-0.6524; 0.6624]        2.7
## Porcu et al. (1998)      0.0221 [-5.5943; 5.6384]        0.1
## Rowland et al. (2005)    0.1526 [ 0.0109; 0.2943]        6.7
## Russo et al. (2003)      0.0605 [ 0.0472; 0.0737]        7.2
## Schleicher et al. (2008) 0.0960 [ 0.0871; 0.1049]        7.2
## Shiferaw et al. (2018)   0.7054 [-1.5224; 2.9333]        0.4
## Tong et al. (2014)       0.0199 [-0.0005; 0.0403]        7.2
## Wilhelm et al. (1998)    0.2634 [ 0.0841; 0.4428]        6.4
## Yang et al. (2012)       0.7362 [-0.4861; 1.9585]        1.1
## Zils et al. (2005)       0.7456 [-0.2159; 1.7072]        1.6
##
## Number of studies combined: k = 25
##
##                             SMD            95%-CI    t  p-value
## Random effects model 0.3771 [ 0.2379; 0.5163] 5.59 < 0.0001
## Prediction interval         [-0.1835; 0.9378]
##
## Quantifying heterogeneity:
##  tau^2 = 0.0689 [0.0349; 0.1353]; tau = 0.2625 [0.1869; 0.3679]
##  I^2 = 99.8%; H = 22.59 [21.69; 23.53]
##
##
## Details on meta-analytical method:
## - Inverse variance method
## - Sidik-Jonkman estimator for tau^2
## - Q-profile method for confidence interval of tau^2 and tau
## - Hartung-Knapp adjustment for random effects model
```

Table 4.1 shows the random effect model of the studies. The effect size in this dataset is based on continuous outcome data. In the result, we can see the individual effect size and the weight of the studies. The total number of studies included is denoted as *(k)*. The overall effect size in our case is *g=0.3771* and its confidence interval is

0.2379; 0.5163. The p-value is < *0.0001*. The lower bound of the 95% confidence interval for I^2 (heterogeneity) is *0.2379.* The random effect model shows that the study is considerable heterogeneity as the I^2 is *99.8%*. Below is the forest plot (Figure 4.2) which shows the effect size according to the studies and where SMD is positive for all the studies.

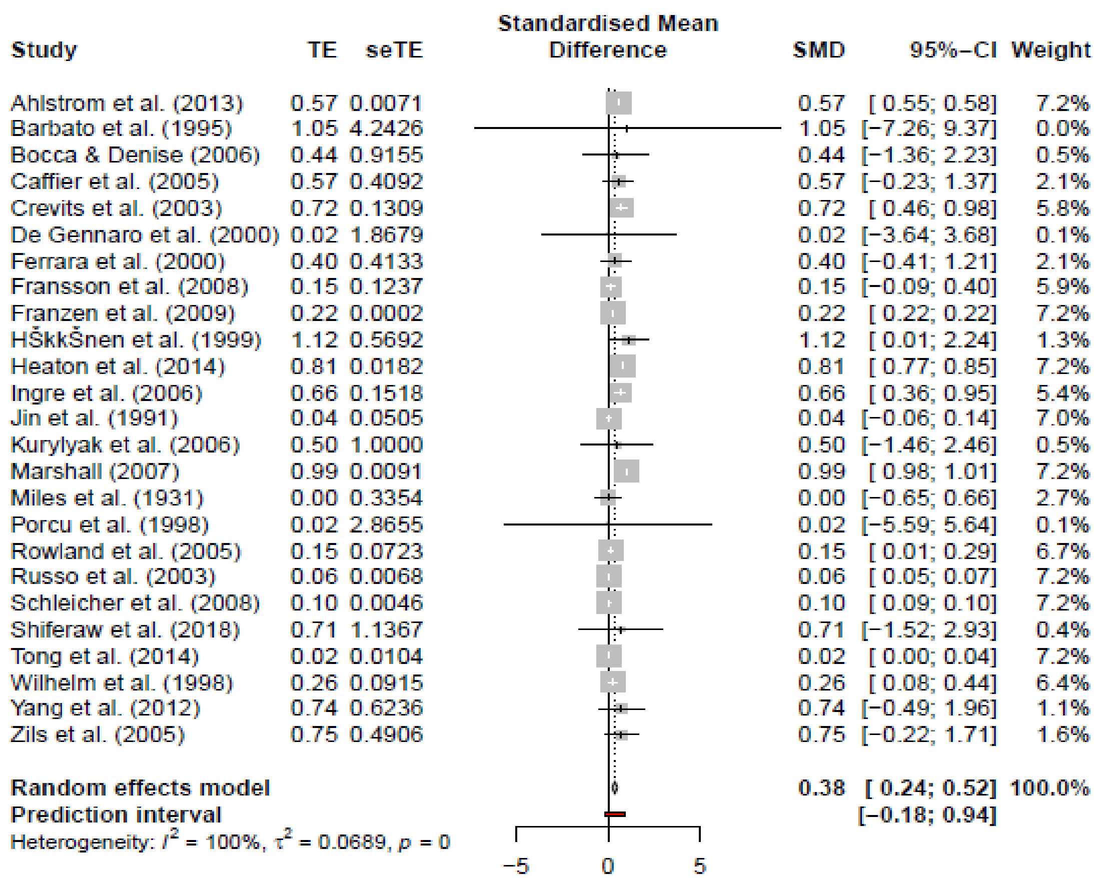

Figure 4.2. Forest plot of the studies

4.2.2. Pooling Effect Size of the Key Metrics. In the random effect model, we want to account for our assumption that the studies show more variance than drawn from a single population. We found 31 unique metrics which are captured in different studies but as the sample size is very small for these unique metrics, we categorized the metrics and found 6 key metrics. We then averaged out the effect sizes and ran the random effect model. Table 4.2 shows the result.

Table 4.2. Pooling effect size of the key metrics

```
## Metrics            SMD            95%-CI %W(random)
## Blink          0.0413 [-1.1809; 1.2636]        1.3
## Fixation       0.1377 [-0.5864; 0.8618]        3.4
## Gaze           0.0169 [-0.2718; 0.3056]       15.3
## Pupil Size     0.0605 [ 0.0156; 0.1054]       42.2
## Saccade        0.0050 [-2.1411; 2.1511]        0.4
## Smooth Pursuit 0.3696 [ 0.2798; 0.4594]       37.3
##
## Number of studies combined: k = 6
##
##                         SMD            95%-CI    t p-value
## Random effects model 0.1714 [-0.0063; 0.3491] 2.48  0.0559
## Prediction interval         [-0.1834; 0.5262]
##
## Quantifying heterogeneity:
##  tau^2 = 0.0116 [0.0028; 0.0876]; tau = 0.1075 [0.0526; 0.2961]
##  I^2 = 86.5% [72.7%; 93.3%]; H = 2.72 [1.91; 3.86]
##
## Test of heterogeneity:
##      Q d.f.  p-value
##  36.93    5 < 0.0001
##
## Details on meta-analytical method:
## - Inverse variance method
## - Sidik-Jonkman estimator for tau^2
## - Q-profile method for confidence interval of tau^2 and tau
## - Hartung-Knapp adjustment for random effects model
```

For the random effect model meta-analysis, there are some parameters we included which are between-study-variance estimator (τ^2), and Knapp-Hartung(-Sidik-Jonkman) adjustment. We used the Sidik-Jonkman estimator ("SJ") and the HKSJ method to get the effect size of the metrics. The output shows that our estimated effect is *g = 0.17* and the 95% confidence interval stretches from *g = 0063 to 0.3491*. Heterogeneity is I^2 *= 86%* which means even though there is high heterogeneity, there is a true effect behind our data.

We compared the output using the DerSimonian-Laird estimator and with the setting hakn = FALSE. As this estimator is the default, we do not have to define method.tau. We saw that the overall effect size is the same as the previous one.

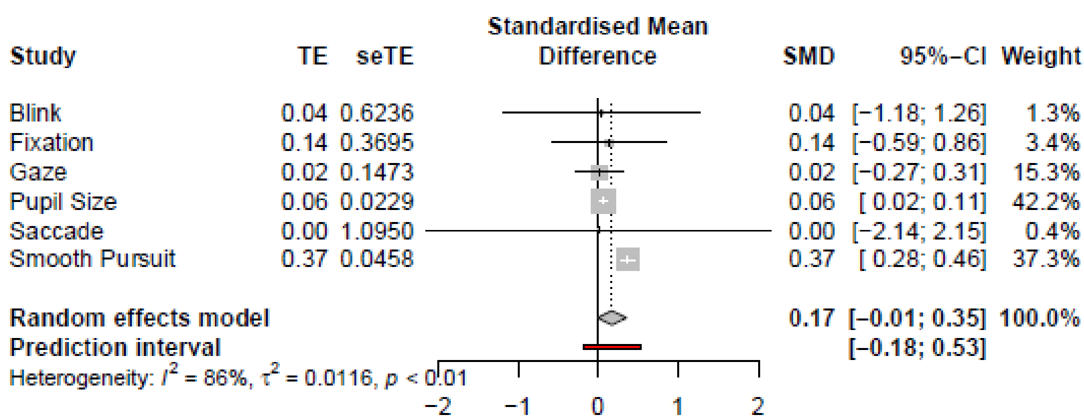

Figure 4.3. Forest plot of the key metrics

In the above forest plot (Figure 4.3), we see the function plotted with a diamond that is the overall effect and its confidence interval as the prediction interval is the red line. The layout is created as a forest plot according to the guidelines of the Journal of the American Medical Association as output.

5. DISCUSSION

This meta-analysis investigates and compares how the number of hours of sleep deprivation correlates with sleepiness. In the study, we also found 6 key metrics which are most effective to capture sleepiness. We also analyze the captured significant metrics which are used to capture sleepiness in the selected studies and found 32 metrics, which can be used for more in-depth analysis.

Sleepiness is regulated by three main factors: the circadian rhythm, time awake, and prior sleep (Ahlstrom et al., 2013). The eye movements of an individual who is awake can take one of three states: blink, saccade, and fixation. Researchers have utilized 6 key eye-tracking metrics to study sleep deprivation and these metrics are discussed below.

5.1. FIXATION

A gaze cluster constitutes a fixation when the eyes are locked toward an object. A fixation is defined as “a relatively stable eye-in-head position within some threshold of dispersion (~2 deg) over some minimum duration (200ms), and with a velocity threshold of 15-100 degrees per second” (Jacob et al., 2003, p. 581).

Sleep deprivation and fixations are closely related. With sleep deprivation, the corrective movement of a fixation becomes larger and less exact than in normal conditions (Miles et al., 1931). Sleep deprivation also reduces the rate of fixations, increases the spatial dispersion of fixations, and increases the randomness of patterns of transitions between fixations (Shiferaw et al., 2018). The fixation rate decreases with sleep deprivation due to a decline in the amount of information sampled when one is sleepy or drowsy (Miles et al., 1931). Long fixation durations may indicate difficulties extracting or processing information from a display element, which takes place when one is sleepy (Fitts et al., 1950; Goldberg et al., 1999).

5.2. GAZE

A gaze refers to a grouping of fixations within a single area of interest. Its associated measures include the number of fixations within a single gaze, the total number of gazes, the frequency of a gaze, and the duration of a gaze, as well as the mean and statistics of those measures (Hendrickson, 1989). A large number of fixations around a gaze point signify instability of the eyes in positioning the gaze. This instability can be observed in sleep-deprived individuals due to their inability to concentrate or focus on a display point or element (Heaton et al., 2014; Miles et al., 1931, Shiferaw et al., 2018; Tong et al., 2014).

5.3. SMOOTH PURSUIT

Smooth pursuit eye movements refer to the movements of the eye to follow a moving target. Smooth pursuit velocity gain refers to the ratio between the eye velocity and the target velocity during smooth pursuit, and the smooth pursuit phase refers to the distance between the gaze and the target (Ahlstrom et al., 2013). Sleep deprivation degrades the moment-to-moment synchronization between the gaze and the target (Ahlstrom et al., 2013; De Gennaro et al., 2000; Ferrara et al., 2000; Fransson et al., 2008; Porcu et al., 1998; Tong et al., 2014), and causes lapses in gaze-target synchronization sensitivity with increased attention loss (Heaton et al., 2014). Franssen et al. (2008) found that as the length of sleep deprivation increases, only smooth pursuit velocity gain continues to degrade as compared to other metrics.

5.4. SACCADE

A saccade is a rapid eye movement from one fixation to another. The characteristic feature of a saccade is that the movement is not smooth but is organized in distinct jumps. These jumps are rapid, and their endpoint cannot be changed once the saccade is initiated.

Several metrics associated with saccadic eye movements that can be triggered by sleep deprivation include saccadic latency (i.e., the delay before the onset of a saccade), saccadic accuracy (i.e., the ratio of the amplitude of the saccade and the amplitude of the target), saccadic amplitude (i.e., the angular distance the eye travels during the saccade), and saccadic peak velocity (i.e., highest velocity in the saccade) (Zils et al., 2005). These metrics are affected by the slowing of neural responsiveness and metabolism due to sleep deprivation. Sleep deprivation generally leads to increased saccadic latency, decreased saccadic accuracy, increased saccadic amplitude and curvature, and decreased saccadic peak velocity (Ahlstrom et al., 2013; Bocca & Denise, 2006; De Gennaro et al., 2000; Ferrara et al., 2000; Fransson et al., 2008; Marshall 2007; Miles et al., 1931; Pilcher & Huffcutt, 1996; Rowland et al., 2005; Russo et al., 2003; Tong et al., 2014; Zils et al., 2005).

5.5. BLINK

Blink frequency (or rate) is the number of times a person blinks in a minute, and blink duration is the complete time from when the eyelid starts moving down until it is fully up again. With sleep deprivation, blinks become relatively slower for the same amplitude. Normal blink frequency is on the order of 9 to 13 per minute in the daytime, which is increased to 20 to 30 per minute under sleep deprivation (Caffier et al., 2005; Russo et al., 2003)

Blink duration and blink frequency are often used in sleep-related studies (Barbato et al., 1995; Bills, 1931; Crevits et al., 2003; Häkkänen et al., 1999; Ingre et al., 2006; Jin et al., 2013; Kurylyak et al., 2011; Marshall, 2007; Schleicher et al., 2008; Shiferaw et al., 2018). We generally blink more frequently and at a slower speed when we are sleepy (Stern, 1990; Stern, 1984). Lapses due to sleepiness can increase errors and variability in cognitive performance (Doran et al., 2001) A relation between subjective sleepiness measured using the KSS, objective indicators of sleepiness based on blinks, and driving performance has been demonstrated (Ingre et al., 2006). With higher KSS levels, the standard deviation of the lateral position is increased, and eye blinks are longer in duration. Blink duration increases with sleep loss as found in several field studies on driving (Kurylyaket al., 2011; Mitler et al., 1997) and in driving simulators (Anderson et al., 2010; Caffier et al., 2005; Schleicher et al., 2008; Wierwille & Ellsworth, 1994). Sleepiness can also be assessed by the duration of eye closure (PERCLOS), which refers to the proportion of the time the eyes are closed (i.e., typically assessed as between 80% to 100% closed) (Jin et al., 2013; Yang et al., 2012).

5.6. PUPIL SIZE

Pupil size is the aperture in an optical system of a human eye. The normal pupil size varies from 2 to 4 mm in diameter in bright light and 4 to 8 mm in the dark. The deeper the sleep, the more the pupil constricts. Pupil diameter is influenced by the arousal system and is a sensitive indicator of sleepiness (Wilhelm et al., 1998).

Pupil diameter changes are a manifestation and representation of sleep deprivation (Franzen et al., 2009; Marshall. 2007; Wilhelm et al., 1998). Pupil changes in size and other pupillometry metrics can be used to deduce changes in cognitive processing (Ellis, 2009). Using an individual's pupil diameter as a baseline, relative changes in pupil size can be a consequence of sleepiness or sleep deprivation. The latency of pupil constrictions increases with sleep deprivation or drowsiness due to reduced neural responsiveness (Rowland et al., 2005; Russo et al., 2003).

6. LIMITATIONS AND FUTURE RESEARCH

There are several limitations in this meta-analysis, which can be addressed in future research.

Firstly, we could analyze the studies based on task performances, such as computer-based task performance and field-based task performance. However, more studies are needed to do so. Different types of measures such as motor, cognitive and facial expressions, and mood can also be included to arrive at more comprehensive results.

Secondly, we can modify the research study based on the devices used in the studies. As in this study, we did not consider device specification. Different devices use different methods to capture different psychological indicators. Researchers need to explore which devices are more capable of capturing more accurate data and have a long list of supporting metrics. Researchers also can include EEG captured data in combination with eye-tracking data. So, a more in-depth analysis can be done.

Thirdly, the type of sleep deprivation and comparisons between the captured data can also be considered for eye-tracking metric identifications. There are three types of sleep deprivation: short-term, long-term, and partial. Although there are few papers available in these categories, a new study design can be planned to capture data associated with these 3 categories. Researchers can plan this study in a laboratory setting by using some computer-based tasks.

Lastly, the measurement for assessing the sleepiness of users in a computer-based environment can be captured. Researchers can analyze the relationship between sleepiness and performance based on task accuracy and response/completion time. We hope that future research will contribute toward the body of research to better explain and understand the relationships between eye-tracking and performance metrics and the underlying mechanisms of sleepiness. Performance metrics such as lapses (i.e., response time > 500 milliseconds) and error types in task completion can also be assessed to determine whether they are appropriate for detecting sleepiness. It will offer useful guidelines to detect sleepiness in the computer-based workplace environment and help enhance workplace productivity and quality of work.

7. CONCLUSION

In this thesis, we carried out a meta-analysis for synthesizing quantitative results of different studies. For the study, we set some criteria to include the papers for analysis, and based on those criteria, we found 25 papers and 58 metrics to analyze. The initial criteria for inclusion were that: (i) studies should be based on eye-tracking metrics, (ii) there should be pre-study and post-study measurements, and (iii) data should be captured when subjects were alert and when the subjects were sleep-deprived.

This research study is mainly focused on finding the most significant eye metrics which can be used to detect sleepiness. These metrics can be identified based on different task performance. We focused that how these metrics differ from an alert state to a sleep-deprived state. We also checked in the studies that the participants have good vision and did not have any sleep-related issues and were not on medication due to sleep problems. We included those studies that meet the above criterion for the meta-analysis.

As a result of this research study, we found that 6 key categories of eye-tracking metrics have been used to assess sleepiness. Even though it is possible to bifurcate those 6 key categories of metrics and break them down for more in-depth analysis, the sample size is very small and some of the metrics were captured in only one study. Hence, we are unable to run the random effect model. The random effect model works under the assumption of exchangeability. This means that in random-effects model meta-analyses, we can draw the conclusion that not only individual study effects deviate from the true intervention effect due to sampling error, but there is also another source of variance introduced because the studies were drawn from a "universe" of the population rather than a single sample. In our meta-analysis, we can see that the heterogeneity between the studies is quite high but between the metrics, the heterogeneity is better, which means there is a true effect in our data.

This study shows the relationship between sleepiness and psychophysiological indicators of oculometries. Based on the meta-analysis results that identify parameters that demonstrate 6 key categories of metrics that have a strong correlation to sleepiness, this study can be expanded to differentiate general cognitive overload fatigue, that is, non-differentiated or non-categorized from the cause of sleepiness to that induced from severe sleep-deprivation. This can potentially establish sleepiness as a single spectrum or multiple wide spectra from fundamentally different causes (sleep-deprived or cognitive or physical overload).

There are several practical implications. Some of the practical scenarios for application are as follows:

- Detect severe sleepiness to provide proactive real-time warnings to forestall critical errors in human-computer interactions.
- Evaluate mental fitness of working personnel for certain job tasks before the start of the shift that involves critical tasks needing sustained mental attention.
- Decide whether to advocate for complete sleep rest or smaller micro-breaks and recommend the frequency of these micro-breaks based on the nature and degree of fatigue.
- Detection of sleepiness of the drivers and alert them to avoid serious road accidents.

BIBLIOGRAPHY

Achermann, P. (2004). The two-process model of sleep regulation revisited. Aviation, Space, and Environmental Medicine, 75(3), A37-A43.

Ahlstrom, C., Nyström, M., Holmqvist, K., Fors, C., Sandberg, D., Anund, A., ... & Åkerstedt, T. (2013). Fit-for-duty test for estimation of drivers' sleepiness level: Eye movements improve the sleep/wake predictor. Transportation Research Part C: Emerging Technologies, 26, 20-32.

Åkerstedt, T., & Gillberg, M. (1990). Subjective and objective sleepiness in the active individual. International Journal of Neuroscience, 52(1-2), 29-37.

Åkerstedt, T., Peters, B., Anund, A., & Kecklund, G. (2005). Impaired alertness and performance driving home from the night shift: a driving simulator study. Journal of Sleep Research, 14(1), 17-20.

Alhola, P., & Polo-Kantola, P. (2007). Sleep deprivation: Impact on cognitive performance. Neuropsychiatric Disease and Treatment, 3, 553–567 (2007).

Anderson, C., Wales, A. W., & Home, J. A. (2010). PVT lapses differ according to eyes open, closed, or looking away. Sleep, 33(2), 197-204.

Anund, A., Kecklund, G., Peters, B., Forsman, Å., Lowden, A., & Åkerstedt, T. (2008). Driver impairment at night and its relation to physiological sleepiness. Scandinavian Journal of Work, Environment & Health, 142-150.

Baddeley, A. D., & Hitch, G. (1974). Working memory. In Psychology of learning and motivation (Vol. 8, pp. 47-89). Academic Press.

Baddeley, A. (2000). The episodic buffer: a new component of working memory?. Trends in Cognitive Sciences, 4(11), 417-423.

Baddeley, A., Cocchini, G., Della Sala, S., Logie, R. H., & Spinnler, H. (1999). Working memory and vigilance: Evidence from normal aging and Alzheimer's disease. Brain and Cognition, 41(1), 87-108.

Barbato, G., Ficca, G., Beatrice, M., Casiello, M., Muscettola, G., & Rinaldi, F. (1995). Effects of sleep deprivation on spontaneous eye blink rate and alpha EEG power. Biological Psychiatry, 38(5), 340-341.

Bera, P., Soffer, P., & Parsons, J. (2019). Using Eye Tracking to Expose Cognitive Processes in Understanding Conceptual Models. MIS Quarterly, 43(4), 1-22.

Bills, A. G. (1931). Blocking: A new principle of mental fatigue. The American Journal of Psychology, 43(2), 230-245.

Bocca, M. L., & Denise, P. (2006). Total sleep deprivation effect on disengagement of spatial attention as assessed by saccadic eye movements. Clinical Neurophysiology, 117(4), 894-899.

Buettner, R., Sauer, S., Maier, C., & Eckhardt, A. (2018). Real-time prediction of user performance based on pupillary assessment via eye tracking. AIS Transactions on Human-Computer Interaction, 10(1), 26-56

Caffier, P. P., Erdmann, U., & Ullsperger, P. (2003). Experimental evaluation of eye-blink parameters as a drowsiness measure. European Journal of Applied Physiology, 89(3-4), 319-325.

Caffier, P. P., Erdmann, U., & Ullsperger, P. (2005). The spontaneous eye-blink as sleepiness indicator in patients with obstructive sleep apnoea syndrome-a pilot study. Sleep Medicine, 6(2), 155-162.

Caldwell, J. A., Caldwell, 1. L., Thompson, L. A., & Lieberman, H. R. (2019). Fatigue and its management in the workplace. Neuroscience and Biobehavioral Reviews, 96, 272-289.

Carskadon, M. A., & Dement, W. C. (2005). Normal human sleep: an overview. Principles and Practice of Sleep Medicine, 4, 13-23.

Chen, S., & Epps, J. (2014). Using task-induced pupil diameter and blink rate to infer cognitive load. Human–Computer Interaction, 29(4), 390-413.

Crevits, L., Simons, B., & Wildenbeest, J. (2003). Effect of sleep deprivation on saccades and eyelid blinking. European Neurology, 50(3), 176-180.

De Gennaro, L., Ferrara, M., Urbani, L., & Bertini, M. (2000). Oculomotor impairment after 1 night of total sleep deprivation: a dissociation between measures of speed and accuracy. Clinical Neurophysiology, 111(10), 1771-1778.

Doghramji, K., Mitler, M. M., Sangal, R. B., Shapiro, C., Taylor, S., Walsleben, J., ... & O'Malley, E. B. (1997). A normative study of the maintenance of wakefulness test (MWT). Electroencephalography and Clinical Neurophysiology, 103(5), 554-562.

Doran, S. M., Van Dongen, H. P., & Dinges, D. F. (2001). Sustained attention performance during sleep deprivation: evidence of state instability. Archives Italiennes de Biologie, 139(3), 253-267.

Drake, C. L., Roehrs, T. A., Burduvali, E., Bonahoom, A., Rosekind, M., & Roth, T. (2001). Effects of rapid versus slow accumulation of eight hours of sleep loss. Psychophysiology, 38(6), 979-987.

Drummond, S. P., Bischoff-Grethe, A., Dinges, D. F., Ayalon, L., Mednick, S. C., & Meloy, M. J. (2005). The neural basis of the psychomotor vigilance task. Sleep, 28(9), 1059-1068.

Durmer, J. S., & Dinges, D. F. (2005, March). Neurocognitive consequences of sleep deprivation. In Seminars in neurology (Vol. 25, No. 01, pp. 117-129). Copyright© 2005 by Thieme Medical Publishers, Inc., 333 Seventh Avenue, New York, NY 10001, USA.

EDHOLM, O. G., & Bacharach, A. L. (1965). The physiology of human survival. The physiology of human survival (Academic Press, 1965.)[Pp. xxii+ 581]. 140s. Ergonomics, 9(6), 539-539.

Eickhoff, S. B., Nichols, T. E., Laird, A. R., Hoffstaedter, F., Amunts, K., Fox, P. T., ... & Eickhoff, C. R. (2016). Behavior, sensitivity, and power of activation likelihood estimation characterized by massive empirical simulation. Neuroimage, 137, 70-85.

Ellis, K. K. E. (2009). Eye tracking metrics for workload estimation in flight deck operations. Theses and Dissertations, 288.

Ferrara, M., Gennaro, L.D., & Bertini, M. (2000). Voluntary oculomotor performance upon awakening after total sleep deprivation. Sleep, 23(6), 801-811.

Fitts, P. M., Jones, R. E., & Milton, J. L. (1950). Eye movements of aircraft pilots during instrument-landing approaches. Aeronautical Engineering Review 9(2), 24–29.

Fransson, P. A., Patel, M., Magnusson, M., Berg, S., Almbladh, P., & Gomez, S. (2008). Effects of 24-hour and 36-hour sleep deprivation on smooth pursuit and saccadic eye movements. Journal of Vestibular Research, 18(4), 209-222.

Franzen, P. L., Buysse, D. J., Dahl, R. E., Thompson, W., & Siegle, G. J. (2009). Sleep deprivation alters pupillary reactivity to emotional stimuli in healthy young adults. Biological Psychology, 80(3), 300-305.

Ghimire, D., Jeong, S., Yoon, S., Park, S., & Choi, J. (2015). Real-time sleepiness detection for driver state monitoring system. Adv. Sci. Technol. Lett, 120, 1-8.

Gidlöf, K., Wallin, A., Dewhurst, R., & Holmqvist, K. (2013). Using eye tracking to trace a cognitive process: Gaze behaviour during decision making in a natural environment. Journal of Eye Movement Research, 6(1):3, 1-14.

Gillberg, M., Kecklund, G., & Åkerstedt, T. (1994). Relations between performance and subjective ratings of sleepiness during a night awake. Sleep, 17(3), 236-241.

Glaholt, M. G., & Reingold, E. M. (2009). The time course of gaze bias in visual decision tasks. Visual Cognition, 17(8), 1228-1243.

Goldberg, J. H., & Kotval, X. P. (1998). Eye movement-based evaluation of the computer interface.In: S. K. Kumar (ed.), Advances in Occupational Ergonomics and Safety (pp. 529–532). Amsterdam: ISO Press.

Goldberg, J. H. & Kotval, X. P. (1999). Computer interface evaluation using eye movements: Methods and constructs. International Journal of Industrial Ergonomics, 24, 631–645.

Häkkänen, H., Summala, H., Partinen, M., Tiihonen, M., & Silvo, J. (1999). Blink duration as an indicator of driver sleepiness in professional bus drivers. Sleep, 22(6), 798-802.

Heaton, K. J., Maule, A. L., Maruta, J., Kryskow, E. M., & Ghajar, J. (2014). Attention and visual tracking degradation during acute sleep deprivation in a military sample. Aviation, Space, and Environmental Medicine, 85(5), 497-503.

Hendrickson, J. J. (1989, March). Performance, preference, and visual scan patterns on a menu-based system: implications for interface design. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 217-222).

Harrison, Y., & Horne, J. A. (2000). Sleep loss and temporal memory. The Quarterly Journal of Experimental Psychology: Section A, 53(1), 271-279.

Hoddes, E., Dement, W. C., & Zarcone, V. (1972). Stanford-sleepiness-scale. Enzyklopädie der Schlafmedizin, 1184.

Horng, W. B., Chen, C. Y., Chang, Y., & Fan, C. H. (2004, March). Driver fatigue detection based on eye tracking and dynamic template matching. In IEEE International Conference on Networking, Sensing and Control, 2004 (Vol. 1, pp. 7-12). IEEE.

Huffcutt, A. I., Roth, P. L., & McDaniel, M. A. (1996). A meta-analytic investigation of cognitive ability in employment interview evaluations: Moderating characteristics and implications for incremental validity. Journal of Applied Psychology, 81(5), 459.

Ingre, M., Åkerstedt, T., Peters, B., Anund, A., & Kecklund, G. (2006). Subjective sleepiness, simulated driving performance and blink duration: Examining individual differences. Journal of Sleep Research, 15(1), 47-53.

Jacob, R. J., & Karn, K. S. (2003). Eye tracking in human-computer interaction and usability research: Ready to deliver the promises. In The Mind's Eye (pp. 573-605). North-Holland.

Jin, L., Niu, Q., Jiang, Y., Xian, H., Qin, Y., & Xu, M. (2013). Driver sleepiness detection system based on eye movements variables. Advances in Mechanical Engineering, 5, 648431.

Johns, M. W. (1991). A new method for measuring daytime sleepiness: The Epworth sleepiness scale. Sleep, 14(6), 540-545.

Johns, M. W. (2000). Sensitivity and specificity of the multiple sleep latency test (MSLT), the maintenance of wakefulness test and the epworth sleepiness scale: failure of the MSLT as a gold standard. Journal of Sleep Research, 9(1), 5-11.

Johnson, L. C., Spinweber, C. L., Gomez, S. A., & Matteson, L. T. (1990). Daytime sleepiness, performance, mood, nocturnal sleep: the effect of benzodiazepine and caffeine on their relationship. Sleep, 13(2), 121-135.

Klauer, S. G., Dingus, T. A., Neale, V. L., Sudweeks, J. D., & Ramsey, D. J. (2006). The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data. Virginia Tech Transportation Institute, Blacksburg, VA. (NTIS No. DOT HS 810 594).

Klumpers, U. M., Veltman, D. J., van Tol, M. J., Kloet, R. W., Boellaard, R., Lammertsma, A. A., & Hoogendijk, W. J. (2015). Neurophysiological effects of sleep deprivation in healthy adults, a pilot study. PloS One, 10(1), e0116906.

Knutson, K. L., Spiegel, K., Penev, P., & Van Cauter, E. (2007). The metabolic consequences of sleep deprivation. Sleep Medicine Reviews, 11(3), 163-178.

Koslowsky, M., & Babkoff, H. (1992). Meta-analysis of the relationship between total sleep deprivation and performance. Chronobiology International, 9(2), 132-136.

Kotval, X. P., & Goldberg, J. H. (1998). Eye movements and interface components grouping: An evaluation method. In: Proceedings of the 42nd Annual Meeting of the Human Factors and Ergonomics Society (pp. 486–490). Santa Monica: Human Factors and Ergonomics Society.

Kretzer, M. & Maedche, A. (2018). Designing social nudges for enterprise recommendation agents: An investigation in the business intelligence systems context. Journal of the Association for Information Systems, 19(12), 1145-1186.

Kripke, D. F., Garfinkel, L., Wingard, D. L., Klauber, M. R., & Marler, M. R. (2002). Mortality associated with sleep duration and insomnia. Archives of General Psychiatry, 59(2), 131-136.

Kronholm, E., Härmä, M., Hublin, C., Aro, A. R., & Partonen, T. (2006). Self-reported sleep duration in Finnish general population. Journal of Sleep Research, 15(3), 276-290.

Krueger, G. P. (1989). Sustained work, fatigue, sleep loss and performance: A review of the issues. Work & Stress, 3(2), 129-141.

Kurylyak, Y., Lamonaca, F., Mirabelli, G., Boumbarov, O., & Panev, S. (2011, May). The infrared camera-based system to evaluate the human sleepiness. In 2011 IEEE International Symposium on Medical Measurements and Applications (pp. 253-256). IEEE.

Li, J., Ngai, G., Leong, H. V., & Chan, S. C. (2016, June). Your eye tells how well you comprehend. In 2016 IEEE 40th Annual Computer Software and Applications Conference (COMPSAC) (Vol. 2, pp. 503-508). IEEE.

Lim, J., & Dinges, D. (2008). Sleep deprivation and vigilant attention. Annals of the New York Academy of Sciences, 1129(1), 305.

Littner, M. R., Kushida, C., Wise, M., G. Davila, D., Morgenthaler, T., Lee-Chiong, T., ... & Kapen, S. (2005). Practice parameters for clinical use of the multiple sleep latency test and the maintenance of wakefulness test. Sleep, 28(1), 113-121.

MACLEAN, A. W., FEKKEN, G. C., SASKIN, P., & KNOWLES, J. B. (1992). Psychometric evaluation of the Stanford sleepiness scale. Journal of Sleep Research, 1(1), 35-39.

Maquet, P. (2001). The role of sleep in learning and memory. Science, 294(5544), 1048-1052.

Marshall, S. P. (2007). Identifying cognitive state from eye metrics. Aviation, Space, and Environmental Medicine, 78(5), B165-B175.

McCormack, H. M., David, J. D. L., & Sheather, S. (1988). Clinical applications of visual analogue scales: a critical review. Psychological Medicine, 18(4), 1007-1019.

Miles, W. R., & Laslett, H. R. (1931). Eye movement and visual fixation during profound sleepiness. Psychological Review, 38(1), 1.

Miley, A. Å., Kecklund, G., & Åkerstedt, T. (2016). Comparing two versions of the Karolinska Sleepiness Scale (KSS). Sleep and Biological Rhythms, 14(3), 257-260.

Mitler, M. M., Miller, J. C., Lipsitz, J. J., Walsh, J. K., & Wylie, C. D. (1997). The sleep of long-haul truck drivers. New England Journal of Medicine, 337(11), 755-762.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Prisma Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Medicine, 6(7), e1000097.

Monk, T. H., Fookson, J. E., Kream, J., Moline, M. L., Pollak, C. P., & Weitzman, M. B. (1985). Circadian factors during sustained performance: Background and methodology. Behavior Research Methods, Instruments, & Computers, 17(1), 19-26.

Naghavi, H. R., & Nyberg, L. (2005). Common fronto-parietal activity in attention, memory, and consciousness: shared demands on integration?. Consciousness and Cognition, 14(2), 390-425.

Ogawa, Y., Kanbayashi, T., Saito, Y., Takahashi, Y., Kitajima, T., Takahashi, K., ... & Shimizu, T. (2003). Total sleep deprivation elevates blood pressure through arterial baroreflex resetting: a study with microneurographic technique. Sleep, 26(8), 986-989.

PA Van Dongen, H., Belenky, G., & M Krueger, J. (2011). A local, bottom-up perspective on sleep deprivation and neurobehavioral performance. Current topics in Medicinal Chemistry, 11(19), 2414-2422.

Philibert, I. (2005). Sleep loss and performance in residents and nonphysicians: a meta-analytic examination. Sleep, 28(11), 1392-1402.

Philip, P., Sagaspe, P., Prague, M., Tassi, P., Capelli, A., Bioulac, B., ... & Taillard, J. (2012). Acute versus chronic partial sleep deprivation in middle-aged people: differential effect on performance and sleepiness. Sleep, 35(7), 997-1002.

Pilcher, J. J., & Huffcutt, A. I. (1996). Effects of sleep deprivation on performance: a meta-analysis. Sleep, 19(4), 318-326.

Porcu, S., Ferrara, M., Urbani, L., Bellatreccia, A., & Casagrande, M. (1998). Smooth pursuit and saccadic eye movements as possible indicators of nighttime sleepiness. Physiology & Behavior, 65(3), 437-443.

Poudel, G. R., Innes, C. R., & Jones, R. D. (2013). Distinct neural correlates of time-on-task and transient errors during a visuomotor tracking task after sleep restriction. NeuroImage, 77, 105-113.

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. Psychological Bulletin, 124(3):372–422.

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. The Quarterly Journal of Experimental Psychology, 62(8), 1457-1506.

Richardson, G. S, Carskadon, M. A, Flagg, W, van den Hoed, J, Dement, W. C, Mitler, M. M. Excessive daytime sleepiness in man: multiple sleep latency measurement in narcoleptic and control subjects. Electroencephalogr. Clin. Neurophysiol., 1978, 45: 621- 627.

Rodrigue, M., Son, J., Giesbrecht, B., Turk, M., & Höllerer, T. (2015, March). Spatio-temporal detection of divided attention in reading applications using EEG and eye tracking. In Proceedings of the 20th International Conference on Intelligent User Interfaces (pp. 121-125).

Rowland, L. M., Thomas, M. L., Thorne, D. R., Sing, H. C., Krichmar, J. L., Davis, H. Q., ... & Alicandri, E. (2005). Oculomotor responses during partial and total sleep deprivation. Aviation, Space, and Environmental Medicine, 76(7), C104-C113.

Russo, M., Thomas, M., Thorne, D., Sing, H., Redmond, D., Rowland, L., Johnson, D., Hall, S., Krichmar, J. & Balkin, T. (2003). Oculomotor impairment during chronic partial sleep deprivation. Clinical Neurophysiology, 114(4), 723-736.

Sanchez, A., Vanderhasselt, M. A., Baeken, C., & De Raedt, R. (2016). Effects of tDCS over the right DLPFC on attentional disengagement from positive and negative faces: An eye-tracking study. Cognitive, Affective, & Behavioral Neuroscience, 16(6), 1027-1038.

Schleicher, R., Galley, N., Briest, S., & Galley, L. (2008). Blinks and saccades as indicators of fatigue in sleepiness warnings: Looking tired? Ergonomics, 51(7), 982-1010.

Shiferaw, B. A., Downey, L. A., Westlake, J., Stevens, B., Rajaratnam, S. M., Berlowitz, D. J., ... & Howard, M. E. (2018). Stationary gaze entropy predicts lane departure events in sleep-deprived drivers. Scientific Reports, 8(1), 1-10.

Shneerson, J. M. (2000). Handbook of sleep medicine. Wiley-Blackwell.

Stern J. (1990). A. Blink and you´ll miss it. Human Factors Society Newsletter, 2, 14-15.

Stern J. A., Walrath, L. C., & Goldstein R. (1984). The endogenous eyeblink. Psychophysiology, 21, 22-33.

Stickgold, R. (2005). Sleep-dependent memory consolidation. Nature, 437(7063), 1272-1278.

St-Onge, M. P., McReynolds, A., Trivedi, Z. B., Roberts, A. L., Sy, M., & Hirsch, J. (2012). Sleep restriction leads to increased activation of brain regions sensitive to food stimuli. The American Journal of Clinical Nutrition, 95(4), 818-824.

St-Onge, M. P., Wolfe, S., Sy, M., Shechter, A., & Hirsch, J. (2014). Sleep restriction increases the neuronal response to unhealthy food in normal-weight individuals. International Journal of Obesity, 38(3), 411-416.

Surridge-David, M., MacLean, A. W., Coulter, M. and Knowles, J. B. Mood changes following an acute delay of sleep. Psychiatry Res., 1987, 22: 149-158.

Thomas, M., Sing, H., Belenky, G., Holcomb, H., Mayberg, H., Dannals, R., ... & Welsh, A. (2000). Neural basis of alertness and cognitive performance impairments during sleepiness. I. Effects of 24 h of sleep deprivation on waking human regional brain activity. Journal of Sleep Research, 9(4), 335-352.

Tong, J., Maruta, J., Heaton, K. J., Maule, A. L., & Ghajar, J. (2014). Adaptation of visual tracking synchronization after one night of sleep deprivation. Experimental Brain Research, 232(1), 121-131.

Van Dongen, H., Maislin, G., Mullington, J. M., & Dinges, D. F. (2003). The cumulative cost of additional wakefulness: dose-response effects on neurobehavioral functions and sleep physiology from chronic sleep restriction and total sleep deprivation. Sleep, 26(2), 117-126.

Van Dongen, P. A., Baynard, M. D., Maislin, G., & Dinges, D. F. (2004). Systematic interindividual differences in neurobehavioral impairment from sleep loss: evidence of trait-like differential vulnerability. Sleep, 27(3), 423-433.

Wierwille, W. W., & Ellsworth, L. A. (1994). Evaluation of driver drowsiness by trained raters. Accident Analysis & Prevention, 26(5), 571-581.

Wilhelm, B., Wilhelm, H., Lüdtke, H., Streicher, P., & Adler, M. (1998). Pupillographic assessment of sleepiness in sleep-deprived healthy subjects. Sleep, 21(3), 258-265.

Yang, F., Yu, X., Huang, J., Yang, P., & Metaxas, D. (2012, September). Robust eyelid tracking for fatigue detection. In 2012 19th IEEE International Conference on Image Processing (pp. 1829-1832). IEEE.

Zils, E., Sprenger, A., Heide, W., Born, J., & Gais, S. (2005). Differential effects of sleep deprivation on saccadic eye movements. Sleep, 28(9), 1109-1115.

VITA

Debasis Roy was born in Garhbeta, West Bengal, India in July 1987. He received his Bachelor’s degree in Electrical Engineering from the West Bengal University of Technology, Kolkata, India. He worked in the telecommunications field from July 2008 to August 2018. He then joined the Business and Information Technology department at the Missouri University of Science and Technology in Spring 2019. He earned two graduate certificates from Missouri University of Science and Technology in Business Analytics and Data Science, and Electronic and Social Commerce in December 2020. In May 2021, he received his MS degree in Information Science and Technology from the Missouri University of Science and Technology.