Development of an objective measure of cognitive workload for rehabilitation using electroencephalography (EEG)

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Abstract

The purpose of rehabilitation following a neurological injury is to reduce impairments, maximize functional abilities, and enhance quality of life. As a part of rehabilitation, patient is assigned a rehabilitation task, and literature suggests this task should be challenging enough to stimulate motor learning and speed up recovery. The challenge level of a rehabilitation task is determined by variables such as the number of repetitions and the intensity of the task. Therefore, it is important for clinicians to consider these variables when setting rehabilitation programs so they can determine how challenging a rehabilitation task is for each individual. This can also help identify the optimal number of repetitions of the task, and the induced cognitive workload to achieve good rehabilitation outcomes for each patient.

In current rehabilitation settings, clinicians lack a clear method to determine how challenging a task is for patients, so they monitor their performance metrics such as task completion rate, response time, and accuracy to adjust task difficulty and induced cognitive workload. Such observation method lacks sensitivity to cognitive workload variations during the task and is prone to human error. This can result in a task difficult enough to induce cognitive overload or easy enough to induce cognitive underload, both of which are detrimental to people with brain injuries and need to be avoided. Therefore, clinicians should be provided with a precise objective method for observing cognitive workload variations during rehabilitation, which may assist clinical observations in making informed decisions about task difficulty and induced cognitive workload. The aim of this thesis is to provide a

framework for selecting and implementing such an objective cognitive workload evaluation method that is appropriate for rehabilitation.

In this thesis, preliminary research was conducted to compare different cognitive workload evaluation methods to highlight their objectiveness. This comparison was based on several parameters such as intrusion, applicability, sensitivity, mobility, and diagnostic power. Based on this comparison, electroencephalogram (EEG)-based event-related potentials (ERPs) were identified as the most suitable method for objectively evaluating cognitive workload. This led to a narrative synthesis of ERP-based cognitive workload evaluation methods which identified key parameters that could influence such methods. Furthermore, this review compared two different types of ERP-based methods, including single-task and dual-task methods, and highlighted single-task ERP-based methods as being more suitable for rehabilitation. However, a limitation of these methods, particularly habituation of the task and stimulus, was also identified in this review.

An experimental study was conducted to validate single-task ERP-based methods to measure cognitive workload by minimizing the effects of habituation. The participants were presented with three difficulty levels of a custom tilt-ball game at random for short periods in anticipation to distribute the effect of habituation across difficulty levels. According to the results, the N1 ERP component amplitude decreased with increasing difficulty and induced cognitive workload, which was in line with the previous literature. This validates the proposed single-task ERP paradigm for measuring cognitive workload despite habituation effects.

A second experimental study was conducted to implement the proposed single-task ERP-based cognitive workload evaluation method in a rehabilitation-like task. The results of second experimental study confirmed the earlier finding that attention orienting response (highlighted by the N1 ERP component) decreased with increasing cognitive workload. Since the task was closer to a rehabilitation task and was more dynamic in nature, the positive results demonstrated the robustness of the proposed single-task ERP-based method for actual rehabilitation tasks. Such a method can help clinicians to gain insight into changes in cognitive workload which can be used to optimize rehabilitation.

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Operational Definitions

Behavioural methods	Behavioral methods assess cognitive workload by examining the outcome or performance observed, such as accuracy, the response time (RT), or task completion.
Cognitive performance	It is the performance of the cognitive processes such as perception, learning, and memory and is linked with individual's skill and physiological state
Cognitive workload	Utilization of brain resources which increases with cognitive workload.
Diagnostic power	Diagnostic power highlights the ability to identify the sources of cognitive workload.
Dual-task methods	An evaluating method which has two task one is primary and other is secondary.
Effort	How hard an individual is "working to achieve defined performance.
Electroencephalogram (EEG)	Electrical activity of brain recorded by special caps/electrodes
Event-related potential (ERP)	Specific potentials in EEG that are linked to a specific event.
Exergames	Exergames incorporate exercises into on-screen computer games
Invasive	An invasive method is one in which the skin is broken in any way during the evaluating process.
Intrusion	Intrusion refers to the degree to which a measuring method interferes with a task's performance.
Neurophysiological methods	Neurophysiological methods use brain signals to evaluate cognitive workload
Non-invasive	A non-invasive method is one in which the skin remains intact during the evaluating process.
Physiological methods	Physiological methods are based on the concept that there is a physiological response (heart rate variability (HRV), blood pressure change, eye blinks, brain signals, skin conductance) to increased cognitive workload.
Processing capacity	Processing capacity is the limit of an individual to process certain information in the brain.
Physical performance	An individual’s ability to carry out physical actions such as maintaining balance, weightlifting, or boxing.

Rehabilitation	Rehabilitation is a process of assessment, treatment, and management by which individuals (and their whanau and caregivers) are supported to reach their maximum potential for physical, cognitive, social, and psychological function, participation in society, and quality of life.
Sensitivity	The ability of a measuring method to detect a variation of cognitive workload during the task
Single-task methods	An evaluating method which has only one task which is primary.
Spatial resolution	Spatial resolution highlights the precision of the evaluating method concerning space.
Subjective methods	Subjective methods use scales to evaluate cognitive workload such as NASA task load index.
Task Demands	What an individual must accomplish and the operating constraints during task completion.
Temporal resolution	Temporal resolution highlights the precision of the evaluating method concerning time.
Visuomotor task	A task which requires both visual and motor functions

Abbreviations

MRT	Multiple Resource Theory
WM	Working Memory
EEG	Electroencephalogram
ERP	Event-related potentials
LRP	Lateralized Readiness Potential
CNS	Central Nervous System
P100	Positive peak at 100ms
P200	Positive peak at 200ms
P300	Positive peak at 300ms
P165	Positive peak at 165ms
N100	Negative peak at 100ms
N200	Negative peak at 100ms
MMN	Miss-Match Negativity
P3a	First subcomponent of P300
P3b	Second subcomponent of P300
N2a	First subcomponent of N200
N2b	Second subcomponent of N200
CPF	Challenge Point Framework
SWAT	Subjective Workload Assessment Technique
NASA-TLX	National Aeronautics and Space Administration Task Load
ISD	Inter Stimulus Distance
ISI	Inter Stimulus Interval
DC	Direct Current (zero frequency)

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature: Date: 14-4-2022

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Denise Taylor ______________________

Chapter 1. Introduction

Rehabilitation is a vital component of recovery after a neurological insult (Carey, 2007). It helps reduce impairments, maximize functional abilities and improve quality of life (Brody, 2012). During rehabilitation, a patient is assigned rehabilitation tasks. Studies have shown that the tasks should be at an optimal level of difficulty to induce a challenging cognitive workload which then stimulates motor learning and speeds up recovery (Akizuki & Ohashi, 2015; Burke et al., 2009; Hung et al., 2016). Guadagnoli and Lee (2004) explored the relationship between cognitive workload and motor learning using a challenge point framework (CPF). Their study suggested presenting a task at the optimal challenge point for each individual to maximize motor learning. In other studies of rehabilitation this has been shown to expedite recovery (Levin & Demers, 2021; Xing & Bai, 2020). The CPF is also supported by evidence in various studies that have verified and confirmed the concept that one achieves maximum motor learning at the optimal challenge point (Akizuki & Ohashi, 2015; Hu et al., 2016; Onla-or & Winstein, 2008). The implication for clinicians is that they should keep track of a patient's optimal challenge point and ensure that rehabilitation tasks are prescribed that are at the right level of difficulty, to maximize recovery.

To set the tasks at an optimal level clinicians need to identify how challenging the task is for patients and how this challenge may change over time. Most commonly, clinicians observe patients' performance metrics such as the task completion rate, response times, and accuracy to adjust the task difficulty and associated cognitive workload. Such a method is prone to human error and lacks sensitivity to cognitive workload variations. For example, a patient may execute a rehabilitation task, having the same *performance* score over two sessions. However, changes in perceived cognitive workload between these sessions might be large and could significantly impact motor learning and recovery (Akizuki & Ohashi, 2015). Furthermore, if the task difficulty is set too high or too low, it can induce cognitive overload or underload, slowing down recovery (Brownsett et al., 2013; McKendrick et al., 2019). During rehabilitation, a precise method is needed to provide clinicians with a measure of cognitive workload variations during the task, which may enhance their clinical observations and improve decisions around task difficulty and associated cognitive workload.

There are several subjective procedures for measuring cognitive workload in other fields. In particular, the modified Cooper–Harper Scale (Wierwille & Casali, 1983), the Subjective Workload Assessment Technique (Reid & Nygren, 1988), and the NASA-TLX are widely used (Hart, 2006; Hill et al., 1992; Rubio et al., 2004). However, these subjective tools are administered only after the task; hence are insensitive to cognitive workload changes that occur during the task or a rehabilitation session (Deeny et al., 2014; Eggemeier, 1988). Furthermore, these tools are lengthy and are subject to subjectivity (Young et al., 2015). Therefore, more objective physiological methods are required, which tap directly into CNS and provide information about cognitive workload variation during the task. The aims and objectives in this thesis are set to address this gap. These aims and objectives are highlighted in upcoming sections, along with an overview of included chapters.

1.1 Aims and objectives of the research

The overarching aim of this Ph.D. is to provide a framework for selecting and testing an objective cognitive workload evaluation method best suited for rehabilitation and provide the basis on which such a method can be implemented. This aim was divided into following objectives

1. To understand the basics of cognitive workload and its evaluation.
    a. Understand the concept of cognitive workload, including theories of attention, performance, and task difficulty.
    b. Compare existing cognitive workload evaluation methods to highlight the best-suited method for rehabilitation.
2. To conduct an extensive review to investigate:
    a. Electroencephalogram (EEG) and Event-Related Potential (ERP)-based methods to evaluate cognitive workload.
    b. The ERP components best correlated to cognitive workload using single-task ERP paradigms.
    c. The parameters of single-task ERP-based cognitive workload evaluation methods which can affect the evaluation criteria of these methods.
3. To conduct an experimental study to:
    a. Provide a framework to address the limitations of the single-task ERP-based method as highlighted in the review.
    b. Validate the efficacy of the single-task ERP methods to evaluate cognitive workload.
4. To conduct an experimental study to validate the possibility of implementing single-task ERP methods to evaluate cognitive workload in a rehabilitation-like task designed with the help of clinicians.

1.2 Structure of the thesis

The thesis structure and key objectives are outlined in **Figure 1.1**.

Chapter 2. Background

This chapter provides preliminary research to highlight the scientific context of objectively evaluating cognitive workload. This chapter is divided into two sections. The first section links the cognitive workload with attention and differentiates it from observable physical performance. The second section elaborates on different cognitive workload evaluation methods and compares them using selection criteria constructed from various parameters.

Chapter 3. Narrative Synthesis

This review examines the current ERP-based methods to evaluate cognitive workload through a narrative synthesis. This narrative synthesis explores and compares different ERP-based methods to evaluate cognitive workload. This chapter also provided an association between individual ERP components and sources of cognitive workload along with the parameters affecting the evaluation criteria of single-task ERP-based methods. This chapter highlights the limitations of single-task ERP-based methods and provides a base for upcoming chapters. A manuscript related to this narrative synthesis has been published in the *Neuroscience & Biobehavioural Reviews.*

Chapter 4. Study 1: A novel ERP paradigm to evaluate cognitive workload.

The narrative synthesis highlighted habituation of stimuli as the limitation of single-task ERP methods to evaluate cognitive workload. An experimental study was designed to validate the efficacy of single-task ERP paradigms by implementing a novel task presentation method to address the effect of habituation. A manuscript related to this chapter has been published in the *International Journal of Psychophysiology.*

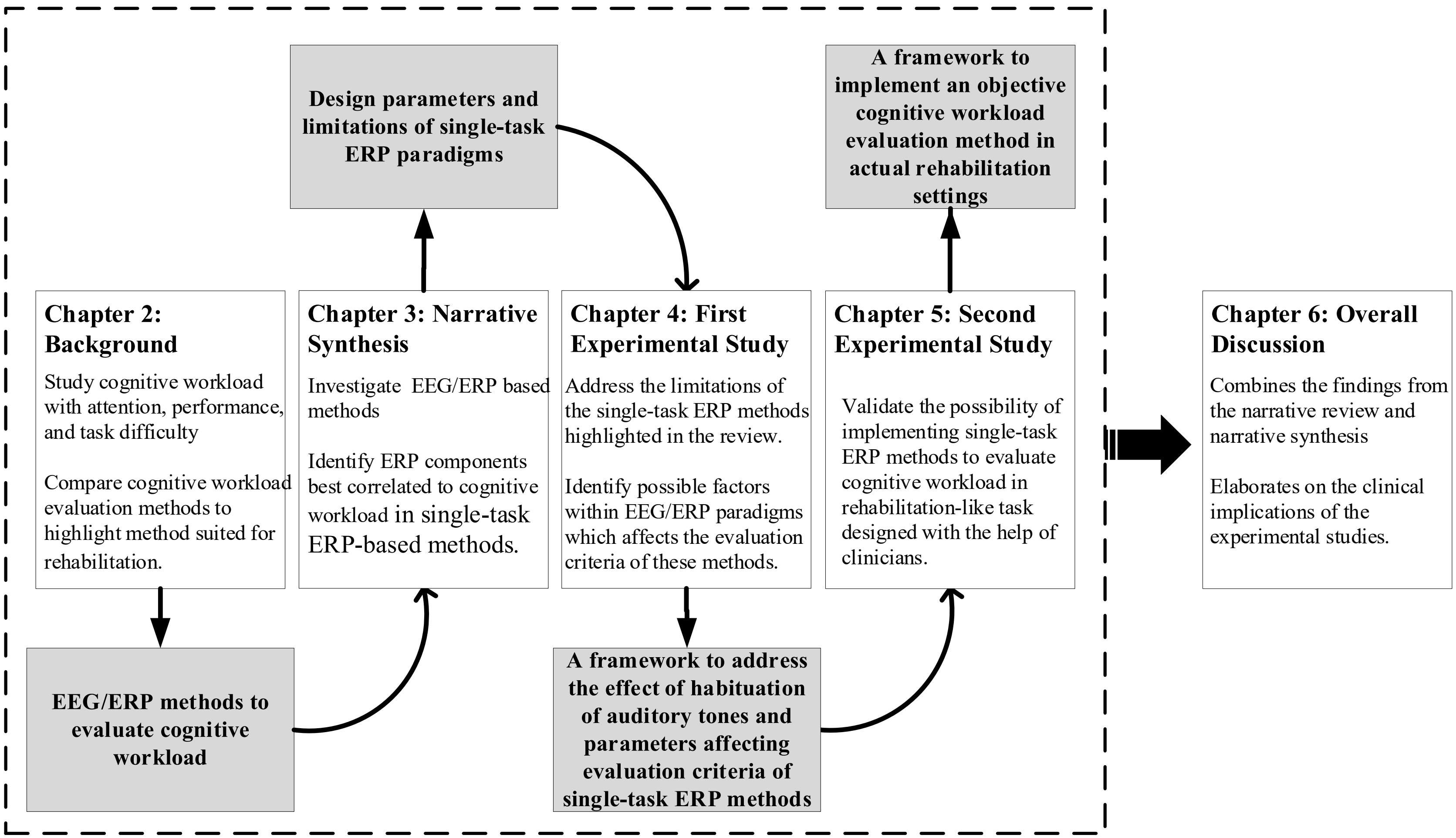

Figure 1.1 Thesis Structure with objectives

Chapter 5. Study 2: Efficacy of the novel ERP paradigm to evaluate cognitive workload during a dynamic balance task.

This study uses a novel balance task designed with the help of clinicians and physiotherapists to validate the efficacy of the single-task ERP-based method presented in the previous chapter. The manuscript has been published in the *Frontiers in Human Neuroscience.*

Chapter 6. Integrated discussion and conclusion

This chapter combines the findings from the preliminary research and narrative synthesis to highlight the gaps and highlight how this thesis addresses these gaps. It then elaborates on the importance and clinical implications of the experimental studies. Limitations and recommendations are provided to guide future research into ERP-based methods in clinical settings.

Chapter 2. Background

2.1 Prologue

This chapter explores the construct of cognitive workload and different cognitive workload evaluation methods. These methods were considered regarding their applicability in real-life situations using distinct criteria constructed from various parameters highlighted in the literature. This chapter specifically addresses the following research objective:

1. To understand the basics of cognitive workload and its evaluation methods.
    c. Understand the concept of cognitive workload.
    d. Identify and compare cognitive workload evaluation methods

2.2 Cognitive workload

2.2.1 Key tenets of Cognitive workload

Research articles about cognitive workload have almost tripled since the 1980s (Young et al., 2015). Despite the popularity of research in this area, there is no specific definition of cognitive workload which applies to every field. There are various definitions of 'cognitive workload' applicable in different domains, as highlighted in **Figure 2.1**. Although the authors of respective domains used different terminologies, there was a degree of acceptance around the following key tenets of cognitive workload.

1. The cognitive workload is the amount of work or effort necessary for a person to complete a task over a given period (Xie & Salvendy, 2000).

2. The cognitive workload cannot be detected directly but can be evaluated through some other variables that correlate highly with it, such as subjective rating, performance, and some physiological data (Carryl, 2012).

3. Cognitive workload has both static and dynamic attributes, for example, the cognitive workload within a time interval and at a single moment.

4. Each individual has limited processing capacity or processing resources. Cognitive workload involves the depletion of processing resources to accomplish the work (Sweller, 1988). A high workload depletes these resources faster than a low workload.

5. The cognitive workload is a multidimensional variable. In Subjective Workload Assessment Technique (SWAT), Reid and Nygren (1988) divided cognitive workload into three dimensions: 1) time load, 2) effort and 3) psychological stress. Similarly, the National Aeronautics and Space Administration Task Load Index (NASA-TLX) developed by Hart and Staveland (1988) defined cognitive workload along six dimensions: cognitive demand, physical demand, temporal demand, performance, frustration level, and effort.

6. The cognitive workload is affected by a variety of factors since it is not merely a property of the task but also of the individual and their interaction with the task (Akizuki & Ohashi, 2015; Carryl, 2012; Hart & Staveland, 1988; Sweller, 1988). Eggemeier (1988) classified the factors that influence cognitive workload into causal factors (which consist of task and environmental variables, operator characteristics, and moderating variables), and effect factors (which contain the difficulty, response, and performance variables)

To sum it up, the cognitive workload is incompletely defined, certainly multifaceted, and based on the key tenets of cognitive workload, directly relates to an individual. These tenets and definitions highlighted in **Figure 2.1** pointed out four key constructs to define cognitive workload 1) task demands, 2) Effort, 3) Performance, and 4) processing capacity. We will illustrate each of these constructs in the following sections using the example of tracking an object in a specified amount of time.

Task Demands

Task demands are defined in terms of what an individual must accomplish and the operating constraints during task completion. According to the literature, the most basic task demands in psychological research are composed of different components (Posner & Raichle, 1994). Some of these components can be cognitive (problem solving), while others can be physical (environmental and physical task constraints). A clear boundary between the physical and cognitive demands is yet to be defined because many real-life tasks impose a physical demand, which in turn places loads on cognitive tasks and cognitive resources (Perry et al., 2008). Accordingly, we defined task demands as constraints, including environmental factors, physiological factors, and the presentation of the task. For example, a tracking task imposes demands such as the number of objects to be tracked, the time in which the objects can be tracked, or the difference in shapes of objects to be tracked.

Effort

The effort is a crucial construct of cognitive workload, which depends on how hard an individual is "working to achieve defined performance." The effort can also be thought of as the engaged proportion of limited processing resources. For example, the effort of an individual performing a tracking task can be measured as the amount of processing resources they spend tracking the objects to meet specific performance criteria (objects per time).

Performance

Performance can be evaluated using both physical and cognitive parameters. van Lummel et al. (2015) defined physical performance as an individual's ability to carry out physical actions such as maintaining balance, weightlifting, or boxing. The cognitive performance on the other hand is linked with individual's skill and physiological state such as problem solving (Tabbarah et al., 2002). Our definition of performance keeps both physical and cognitive performance in mind, describing how an individual accomplishes a task depending on its requirements. For example, the number of objects tracked at a specific time by an individual.

Processing Capacity

Processing capacity is the limit of an individual to process certain information in the brain. For example, the amount of attention one can devote to the task from a limited attentional reserve (Kahneman, 1973). This capacity is not fixed and changes based on an individual's physiological state (Wickens, 1991). For example, from a limited processing capacity, an individual may be able to devote a certain amount of processing resources to tracking objects depending on their physiological state.

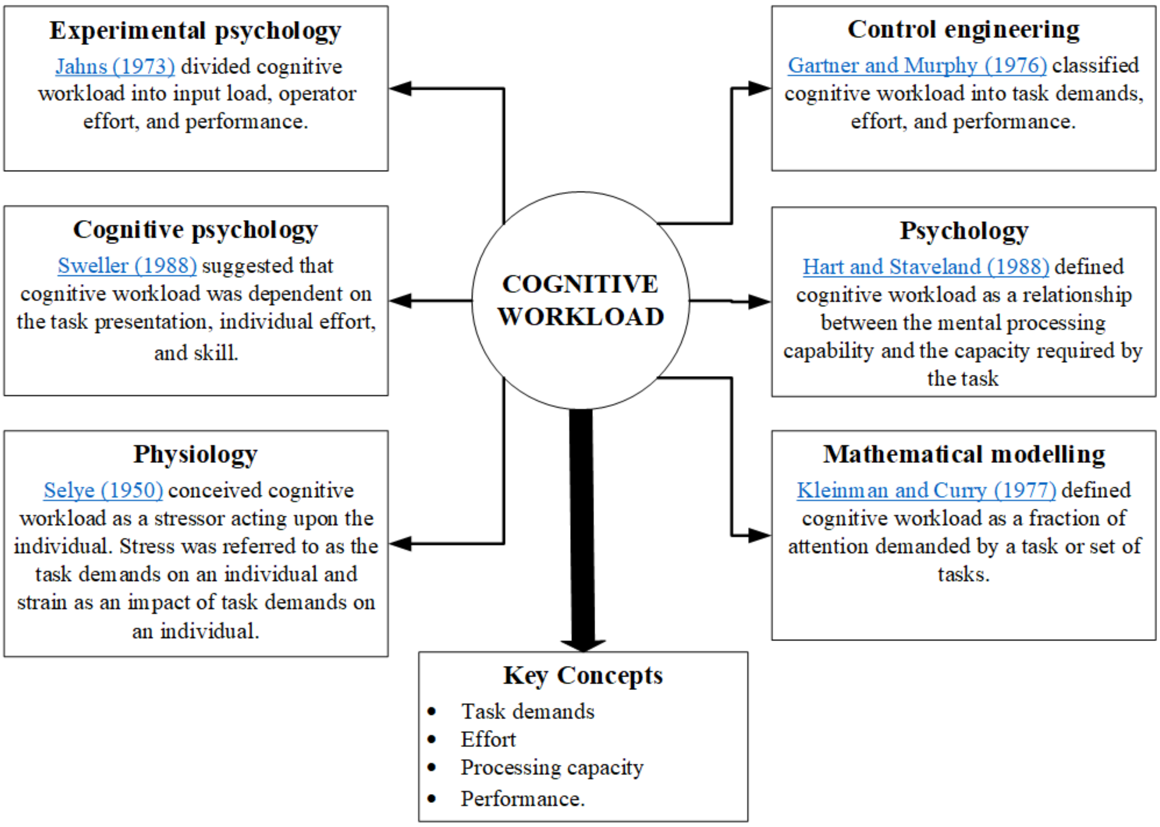

Figure 2.1 Cognitive workload definitions

2.2.2 Proposed cognitive workload definition

Combining the tenets of cognitive workload with the abovementioned constructs, I defined cognitive workload in this thesis as the "amount of attentional resources occupied from a limited attentional reserve during the performance of a task." This amount of occupied attentional resources depends on the task difficulty and the individual's processing capacity. **Figure 2.2** presents a conceptual overview of the proposed cognitive workload definition where processing resources are on the y-axis, and task difficulty is on the x-axis. More resources are occupied as the task difficulty increases, but the performance remains constant until the maximum capacity of an individual. The **Figure 2.2** shows three tasks with Task 3 being the most challenging and requiring most of the brain resources. The performance of Task 1 and Task 2 is the same because they are within the maximum capacity limit. In contrast, Task 3 requires more resources than the maximum capacity limit, so the performance is degraded, as highlighted by the red bar in **Figure 2.2**.

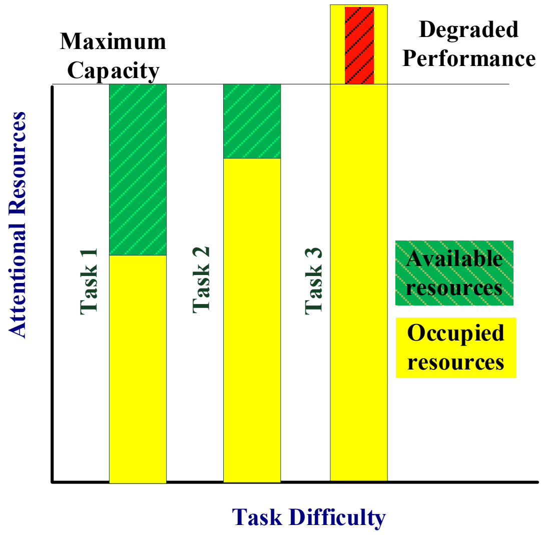

Figure 2.2: Definition of cognitive workload

Cognitive workload is a multidimensional, multifaceted construct that can fluctuate rapidly during the task depending on various factors such as task complexity and the individual's physiological state (Parasuraman et al., 1998). Therefore, it is logical to assume that it is impossible to get a single method of measuring cognitive workload that can cover all the cognitive workload facets. To date, numerous methods to evaluate cognitive workload have been proposed. These methods will be explained in the upcoming sections.

2.2.3 Methods to evaluate cognitive workload.

Since the introduction of cognitive workload as a concept in the 1970s, multiple methods to evaluate this concept have been developed (Baldwin & Coyne, 2005; Baldwin et al., 2004; Brown, 1965; Casali & Wierwille, 1983, 1984; Wierwille & Connor, 1983). These methods to evaluate cognitive workload are divided into 1) Behavioural methods, 2) Subjective methods, and 3) Physiological methods (O'Donnell & Eggemeier, 1986; Wierwille & Eggemeier, 1993). Each method has its benefits and can be compared based on four defined parameters 1) sensitivity and 2) intrusion, 3) diagnostic power, and 4) applicability (Kramer, 1991; O'Donnell & Eggemeier, 1986).

- **Sensitivity** refers to the ability of a measuring method to detect a variation of cognitive workload during the task (O'Donnell & Eggemeier, 1986; Waard, 1997).

- **Intrusion** refers to the degree to which a measuring method interferes with a task's performance (Longo, 2015).

- **Diagnostic power** highlights that in addition to identifying changes in cognitive workload variations, the method should also identify the reasons for those changes. (O'Donnell & Eggemeier, 1986).

- **Validity** highlights that the method must only be sensitive to cognitive workload and not to other variables such as physical workload or emotional stress (Valdehita et al., 2004).

- **Reliability** implies a consistent representation of cognitive workload.

- **Applicability** highlights the feasibility of implementing the measuring method in real-life tasks (Waard, 1997).

Selection Criteria for cognitive workload evaluation methods

Each measurement technique has its advantages and disadvantages and, they are appropriate for different contexts. Based on the literature, an objective evaluation method to be implemented in real-life tasks must have low intrusion, high sensitivity, high diagnostic power, high validity and reliability, and high applicability (Akizuki & Ohashi, 2015; Allison & Polich, 2008; Carryl, 2012; Causse et al., 2015; Cook et al., 2008; Davies et al., 2013; Hart, 2006; Horat et al., 2016; Onla-or & Winstein, 2008; Young et al., 2015). Further sections will elaborate on the cognitive workload evaluation methods presented in **Figure 2.3** and highlight each method's pros and cons based on the selection criteria.

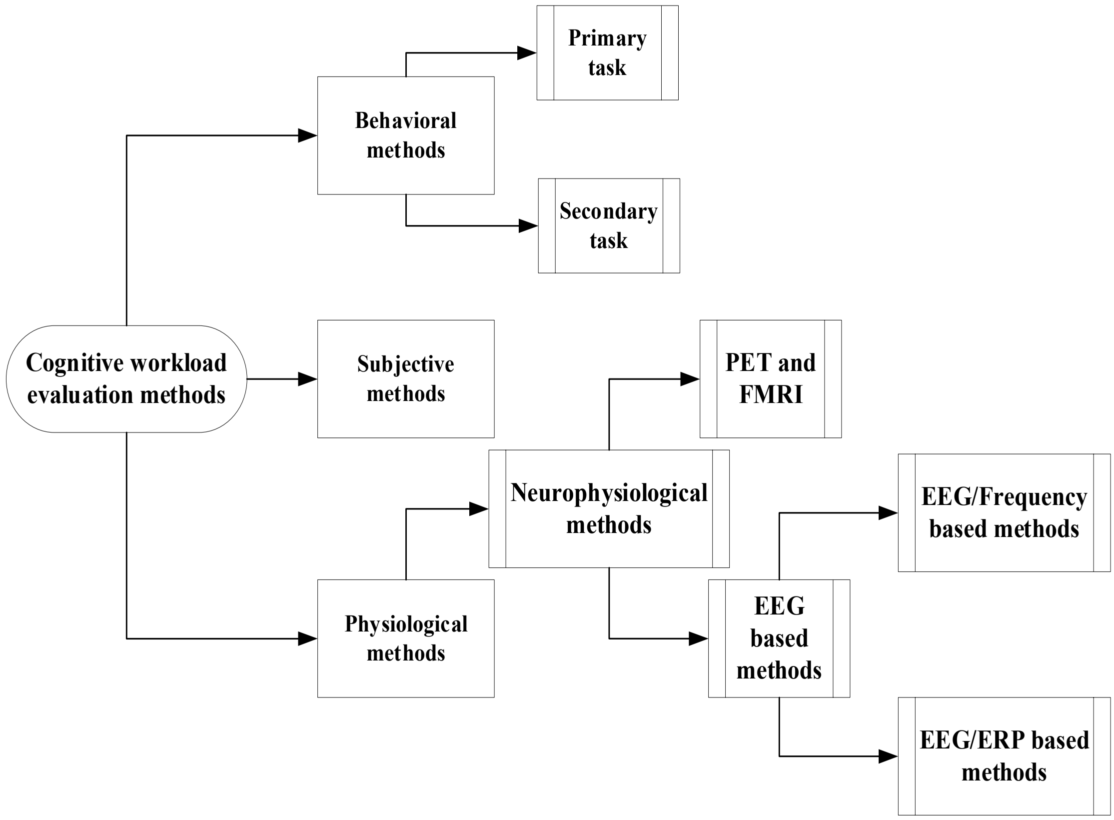

Figure 2.3 Cognitive workload evaluation methods

Behavioral Methods

Behavioral methods assess cognitive workload by examining the outcome or performance observed, such as accuracy, the response time (RT), or task completion (Carryl, 2012). There are two major behavioral methods 1) the primary task method (Direct) and 2) the secondary task method (Indirect).

Primary task methods

In this method, the cognitive workload of the task is measured directly using observable performance. As an example, the observable performance of an individual playing

Tetris is their game score. The task's observable performance can assess how well the participant can perform a particular task, but it cannot provide information about its cognitive workload (Eggemeier, 1988; Knowles, 1963; Meshkati, 1988; Ogden et al., 1979). Primary task methods are the simplest and most direct methods to evaluate cognitive workload. Although they are low intrusive, simple, and functional, they lack sensitivity and cannot measure cognitive workload changes during the task (Eggemeier, 1988).

Secondary task methods implement dual-task paradigms and are considered more robust than primary task methods (Ogden et al., 1979). Dual-task paradigms are based on the resource theory of cognitive workload, which states that humans have limited resources to attend to a particular task (Kahneman, 1973). There are two tasks in secondary task measures; one is the task of interest (i.e., driving, playing a game, speech recognition, or piloting), defined as the **primary task.** Another task is the **secondary task** (i.e., counting, mathematical calculations), which participants perform simultaneously as the primary task. The participants are instructed to focus on the primary task as this is the task they need to complete. As a result, participants spend most of their attention (brain resources) on the primary task to accomplish it. The performance of the secondary task is then used as an index of cognitive workload. These methods are sensitive to the workload changes but can be intrusive as the secondary task can interfere with the primary task. Performance-based methods are unreliable because they rely on factors that can't be controlled, such as level of skill and physiological state.

Subjective methods

Subjective methods are used extensively to assess cognitive workload (Lee et al., 2002; Meshkati, 1988; Srinivasan & Jovanis, 1997; Vidulich & Wickens, 1986). Several scales have been used, and their psychometric properties compared (Hendy et al., 1993; Hill et al., 1992; Rubio et al., 2004). These scales have been categorized into two groups unidimensional and multidimensional.

Unidimensional rating scales

Unidimensional rating scales are considered the simplest to use because there are no complicated analysis techniques (Young et al., 2015). These unidimensional scales have only one dimension and utilize a rating scale to measure overall cognitive workload. For example, the Overall Workload scale (OW) used a unidimensional scale from 0 to 100 where zero represents very low workload, and 100 represents high workload (Hill et al., 1992). Similarly, the Modified Cooper-Harper scale (MCH) utilized a 10-point unidimensional rating scale to measure global workload (Harris, 2000). Although unidimensional scales are easy to implement and are less time-consuming, these scales fail to adapt to the vast diversity in modalities of different tasks, mental operations involved, and various response modes of different tasks (O'Donnell & Eggemeier, 1986).

Multidimensional rating scales

The multidimensional rating scales are a more complex and time-consuming form of measurement and have three to six dimensions (Hill et al., 1992). These scales are the most widely used and are generally more indicative of cognitive workload variations (Waard, 1997). There are two most used multidimensional rating scales to evaluate cognitive workload. First, the NASA-Task Load Index (NASA-TLX) includes six subscales exploring the cognitive workload, physical demand, temporal demand, performance, effort, and frustration level (Hart & Staveland, 1988). Second, the subjective workload assessment technique (SWAT) describes three dimensions of operator workload: time Load, mental effort load, and psychological stress load (Reid & Nygren, 1988). Generally, the multidimensional form of measurement takes more time to complete, but the multidimensional nature of the scales provides a more in-depth analysis of the many aspects of workload (Hart & Staveland, 1988; Hill et al., 1992; Waard, 1997).

Subjective methods are low-cost and easy to implement. Still, several limitations are associated with subjective measures, such as they are usually situation-specific and may fail to consider additivity, learning, experience, and emotional state (Longo, 2015; Pereira da Silva, 2014). Subjective measures are usually administered after the task and thus fail to give cognitive workload information *during* the task (O'Donnell & Eggemeier, 1986). These subjective measures have a very low sensitivity to cognitive workload changes and cannot differentiate between the workload of primary and secondary tasks (Baldwin et al., 2004). These methods lack diagnostic power as they cannot identify the sources of cognitive workload (physical or cognitive). Also, their reliability and validity can be affected by the task. Valdehita et al. (2004) reported that the more extended tasks reduce both reliability and validity of subjective methods.

Physiological methods

Physiological methods are based on the concept that there is a physiological response to increased cognitive workload (Galante et al., 2018). Physiological methods use different physiological measures to evaluate cognitive workload, such as heart rate variability (HRV), blood pressure, eye blinks, brain signals, skin conductance (Collins et al., 2005). Butmee et al. (2019) summarized a review of the literature on cognitive workload by categorizing the use of physiological measures into two groups: 1) four measures used (brain, eye, cardiac, and muscle function) and 2) five measures used (cardio, respiratory, speech, and eye functions) .Various researchers also use only one physiological measure to evaluate cognitive workload, for example, heart rate variability (HRV) (Delliaux et al., 2019; Hjortskov et al., 2004; Wang et al., 2005) or brain signals (Allison & Polich, 2008; Horat et al., 2016; Miller et al., 2011).

Table 2.1 selection criterion for cognitive workload evaluation methods

Methods	**Selection criterion**				
	High sensitivity	Less intrusion	Reliable	High applicability	High diagnostic power
Behavioral Methods	✗	✓	✗	✓	✗
Subjective Methods	✗	✓	✓/✗	✓	✗
Physiological Methods	✓	✓	✓/✗	✓/✗	✓

✓ Present ✗ Not Present ✓/✗ Situation specific

Physiological methods have higher sensitivity than behavioral and subjective methods, are highly diagnostic, and provide information about workload changes during the task (Carryl, 2012). Still, their validity and reliability depend on the experimental setup and the physiological measures used (Brookings et al., 1996). Furthermore, the applicability of these methods is also situation specific. These methods require specialized equipment and special training to operate and interpret the data (McKendrick et al., 2019). **Table 2.1** highlights the cognitive workload evaluation methods and the selection criterion as mentioned earlier. One of the most advocated physiological measures of cognitive workload is brain signals, commonly known as neurophysiological methods (Just et al., 2003; Kramer, 1991; Parasuraman, 2003). These methods was used extensively to evaluate cognitive workload based on the assumption that higher cognitive workload is linked with higher brain activation (Allison & Polich, 2008; Carryl, 2012; Causse et al., 2015; Deeny et al., 2014; Dyke et al., 2015a; Eggemeier, 1988; Horat et al., 2016). These neurophysiological methods will be explained in detail in the coming sections.

Neurophysiological methods

Neurophysiological methods use brain signals to evaluate cognitive workload and have several advantages over other measures. Generally, the most precise cognitive workload measurement comes directly from measuring the brain's activity (Brookings et al., 1996). Neurophysiological methods are more sensitive to cognitive workload variation and can provide real-time cognitive workload assessment (Kramer et al., 1987). A range of neurophysiological cognitive workload evaluation methods vary in a) Invasiveness, b) Spatial resolution, c) temporal resolution, and d) portability.

- **Invasiveness:** This thesis defines an invasive method as one in which the skin is broken in any way and a non-invasive method as one in which the skin remains intact during the evaluating process.

- **Spatial resolution** highlights the precision of the evaluating method concerning space.

- **Temporal resolution** highlights the precision of the evaluating method concerning time.

- **Portability** defines how portable an evaluation method is.

Selection Criteria for neurophysiological methods

A selection criterion for neurophysiological methods to evaluate cognitive workload during real-life tasks can be made based on the above-defined characteristics. A method with less invasiveness, high temporal resolution and high portability is preferred for real-life tasks (Deeny et al., 2014; Galante et al., 2018; Miller et al., 2011). Ideally, having a high spatial resolution should be added to the selection criterion, but there is a trade-off between temporal and spatial resolution (Mehta & Parasuraman, 2013). For example, by increasing the spatial resolution (to highlight active brain regions during the task), we will lose the timing information about *when* the brain signals changed during a task. As timing information is more critical while evaluating cognitive workload (Carryl, 2012), high temporal resolution is preferred and considered the key characteristic of evaluating cognitive workload in real-life tasks. Based on this selection criterion, neurophysiological methods are divided into three main categories 1) PET and fMRI-based methods, 2) fNIRS-based methods, and 3) EEG-based methods. **Figure 2.4** highlights these categories for spatial resolution, temporal resolution, and portability.

PET and fMRI-based methods

Positron emission tomography (PET) evaluates physiological measures such as blood flow, metabolism, radiolabelled drugs, and neurotransmitters (Bailey et al., 2005). This measure is based on injecting and administering a radioactive tracer. Although PET offers reliable spatial resolution, it is invasive, lacks portability, and has a low temporal resolution (Kramer, 1991; Mehta & Parasuraman, 2013). These properties make it unsuitable for measuring cognitive workload.

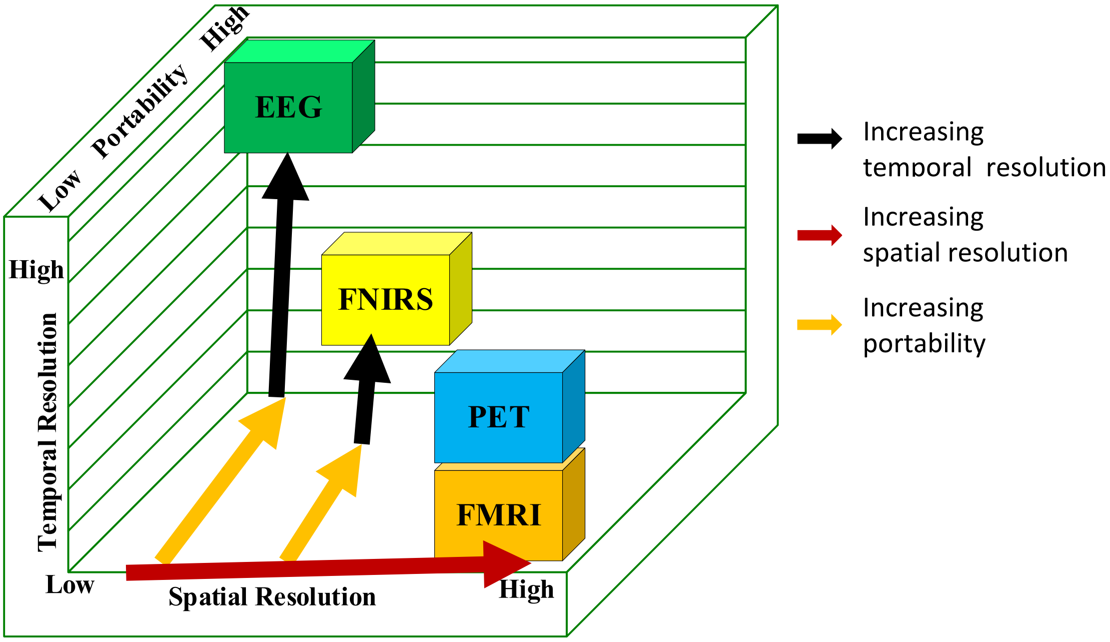

Figure 2.4 EEG vs. PET and fMRI based on the temporal and spatial resolution with portability.

Functional Magnetic Resonance Imaging (fMRI) measures blood flow changes in response to brain activity (Logothetis et al., 2001). These measures offer robust spatial resolution capabilities and highlight which brain areas were active during the task. However, fMRI lacks temporal resolution and portability (Mehta & Parasuraman, 2013). These properties make it unsuitable for assessing performance in real-life tasks. Both PET and fMRI can be seen in **Figure 2.4** concerning their temporal resolution, spatial resolution, and portability.

Functional Near-Infrared Spectroscopy (fNIRS)

Functional Near-Infrared Spectroscopy (fNIRS) measures the oxygenated (HbO2) and deoxygenated (HHb) haemoglobin in the blood supply of the brain (Pfeifer et al., 2018). This method is relatively new, and the advantages of fNIRS lay at the intersection of the disadvantages of fMRI and EEG/ERP based methods (Chiarelli et al., 2017), as highlighted in **Figure 2.4**. fNIRS has a better temporal resolution, is easier, and more cost-effective to implement than fMRI and PET (but spatial resolution is more limited). In comparison, fNIRS has better spatial resolution than EEG/ERP (but the temporal resolution is more limited) (Wilcox & Biondi, 2015). Based on the defined criterion, the method with the highest temporal resolution is defined as the critical characteristic of a method to evaluate cognitive workload; therefore, EEG based methods are considered to be most efficient for evaluating cognitive workload during real-life tasks (Mehta & Parasuraman, 2013; Singleton et al., 1971).

Electroencephalography (EEG)

Electroencephalography (EEG) based methods use the brain's electrical activity to evaluate cognitive workload (Kramer, 1991). Special devices, namely EEG caps, amplifiers, and computers, shown in **Figure 2.5A**, are used to record EEG signals. EEG caps have special electrodes positioned according to the International 10–20 system (Towle et al., 1993). These electrodes record brain activity in voltage fluctuations and send it to special EEG amplifiers to amplify the signal (Light et al., 2010). These amplified signals are then sent to a recording computer, where this raw EEG data is saved. A typical raw EEG signal is shown in **Figure 2.5B,** where electrode names (according to the 10-20 system) are on the y-axis and time is on the x-axis.

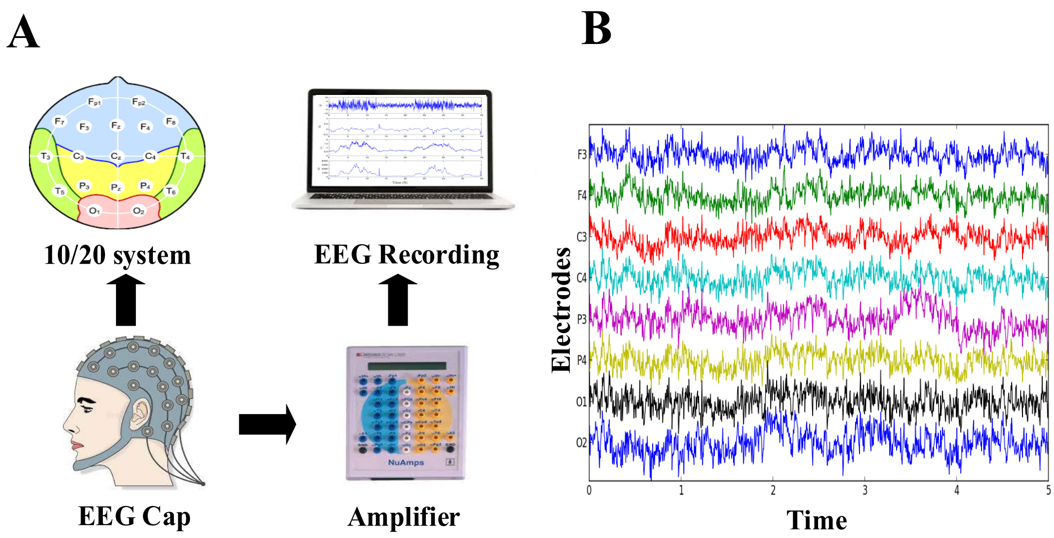

Figure 2.5 (A) EEG recording setup. **(B)** typical EEG signal

EEG offers reliable temporal resolution and can provide information about workload changes during the task's performance (Mehta & Parasuraman, 2013). Although EEG offers low spatial resolution, it is non-invasive with high portability and strong temporal resolution (Knaepen et al., 2015). These properties make it one of the most suitable neurophysiological methods to evaluate cognitive workload during the task. Therefore, EEG measures have been used extensively for cognitive workload assessment (Cranford et al., 2004; Hohnsbein et al., 1995; Käthner et al., 2014a; Muller-Gass et al., 2006; Ullsperger et al., 2001). **Table 2.2** highlights the selection criterion for neurophysiological-based methods to evaluate cognitive workload.

Table 2.2 Selection criterion for Neurophysiological methods.

Neurophysiological Methods	**Selection criterion**			
	High temporal resolution	High portability	High applicability	Non invasive
PET-based Methods	✗	✗	✗	✗
fMRI-based Methods	✗	✗	✗	✓
fNIRS based methods	✗	✓	✓	✓
EEG-based Methods	✓	✓	✓	✓

EEG-based methods and cognitive workload

There are two types of EEG-based cognitive workload evaluation methods available in the literature 1) Frequency-based methods and 2) ERP-based methods. Both methods have their advantages and disadvantages and have been used extensively to evaluate cognitive workload.

Frequency-based methods.

EEG is typically described in terms of a rhythmic activity divided into different frequency bands such as Delta (up to 4Hz), Theta (4 to 8 Hz), Alpha (8 to 15Hz), Beta (15 to 32Hz), and Gamma (> 31Hz) (Newson & Thiagarajan, 2019). Each frequency band has a particular distribution over the scalp and has its biological significance (Saby & Marshall, 2012). These frequency bands are shown in **Figure 2.6**, and their characteristics are outlined in **Table 2.3**.

Table 2.3 Characteristics of EEG frequency bands

Band	Frequency	Location	Characteristics
Delta	Less than 4Hz	frontally in adults, posteriorly in children	High amplitude waves. Slow waves, evident in sleep.
Theta	4Hz to 8Hz	Somatosensory cortex	Displays during cross-modal sensory processing, short-term memory matching of recognized objects.
Alpha	8Hz to 15Hz	posterior regions of the head, both sides,	relaxed/reflecting closing the eyes Also associated with inhibition control,
Beta	16Hz to 31Hz	both sides, symmetrical distribution, most evident frontally	low-amplitude waves active thinking, focus, high alert, anxious.

A number of studies have demonstrated a correlation between work or memory load and power in specific EEG frequency bands, particularly alpha (8-12 Hz) and theta (4-8 Hz) (Koyaş et al., 2014). It is known that alpha is associated with resting (Pfurtscheller et al., 1996), default mode brain activity (Jann et al., 2009), and cortical inhibition (Brouwer et al., 2009), which would indicate why alpha power varies with cognitive workload. A higher cognitive workload, for instance, will make the brain work harder to move out of its resting state (reducing or removing Alpha activity). Therefore, in the literature, the Alpha band was described as a marker of psychological effort and a decrease in alpha power was generally associated with an increase in arousal, resource allocation, or cognitive workload (Fink et al., 2005; Pfurtscheller et al., 1996). The exact cortical location of alpha reduction varied based on the individual's psychological state and the task used (Klimesch et al., 2000). For example, Alpha reduction was seen in parietal regions during effortful and attentive processing in a task that required participants to make series of target judgments and critical estimates based on the provided information (Keil et al., 2006). On the other hand, the Alpha activity was observed in the anterior cortical regions during sleepiness and inattention.(Cantero et al., 2002). Theta band activity has been associated with working memory processes or mental effort in several reviews by Klimesch (1996; 1997; 1999). They reported that a large increase in theta power was associated with an increase in task demands and workload. Numerous other studies have also reported an increase in Theta band activity over the frontal locations with an increase in task demands (Esposito et al., 2009; Jensen & Tesche, 2002; Raghavachari et al., 2001). For example, Raghavachari et al. (2001) used a working memory task and reported a large increase in the theta activity as participants performed the task compared to the baseline (no task).

All above mentioned studies used either Alpha or Theta activity as a measure of cognitive effort, resource allocation (working memory), or cognitive workload and reported an increase in theta power and a decrease in Alpha power with increased cognitive effort. A number of studies also used Alpha and theta simultaneously as a measure of cognitive workload (Brookings et al., 1996; Fournier et al., 1999; Käthner et al., 2014b). They all reported similar trend with increased cognitive workload (increased Theta, decreased alpha). In addition to the changes in alpha and theta bands, power in Beta band has been reported to respond to varying workload. For example, with an increase in cognitive workload, Beta waves have been shown to replace Alpha waves

(Dasari et al., 2017), suggesting that Beta power increased with an increase in task complexity (Brookings et al., 1996).

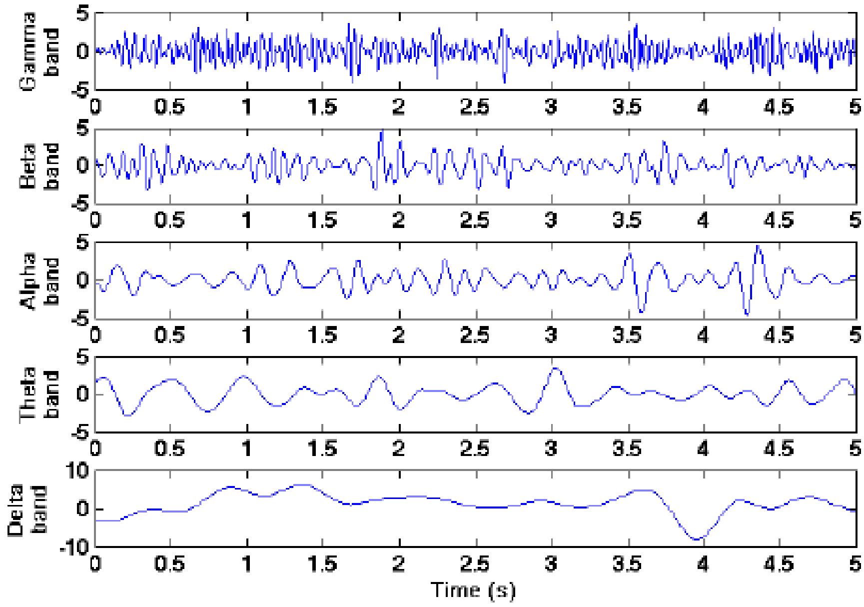

Figure 2.6 Different frequency bands of EEG (Abo-Zahhad et al., 2015)

Although the frequency-based methods provide cognitive workload evaluation evidence, they lack temporal information (Koenig et al., 2001), a vital characteristic of a cognitive workload evaluation method to be implemented in real-life tasks (Young et al., 2015). On the other hand, ERPs have the advantage of having a high temporal resolution, enabling them to examine the neural events responsible for the cognitive workload variation on a millisecond-by-millisecond basis (Sokhadze et al., 2017; Woodman, 2010). Another advantage of ERPs is that they are capable of determining how a specific experimental manipulation affects processing (Luck, 2012). For example, Since we only record the activity relating to the stimuli, we can see how any change in stimuli impacts the processing. Furthermore, ERP-based methods are more robust due to the fact that they can eliminate non-relevant neutral activity (due to averaging), which may not be the case with other scanning techniques (neuroimaging and EEG).

ERP-based methods.

Event-related potentials (ERPs) are linked to a specific event in EEG (Rugg, 1995). These events are marked in the EEG waveform, and after this event, the EEG waveform represents event/stimulus processing within the CNS, known as ERP activity (Luck et al., 2000). This ERP activity is changing rapidly in time and across cortical topographic fields (Carryl, 2012). It is recorded with high temporal resolution in the order of several milliseconds from different scalp locations (Aaronson, 2013).

It is particularly useful to use ERP studies to measure cognitive workload as they provide temporal information about processes such as attention (Sokhadze et al., 2017). For example, early ERP components such as P100, N100, and P200 usually relate to attentional selection mechanisms (Sculthorpe et al., 2008; Takeda et al., 2016), whereas later components (P300) have more to do with stimulus interpretation and response organization (Allison & Polich, 2008; Deeny et al., 2014; Horat et al., 2016). Furthermore, ERP components can be categorized as short-latency or long-latency ERPs, which reflect early stage, modality-specific and late-stage polymodal associative processing, respectively (Sokhadze et al., 2017). Exogenous ERP components (e.g., P100, N100) are modulated by physical attributes of the stimulus (like brightness or loudness), rather than by endogenous cognitive processes (Sur & Sinha, 2009b).

The attention process, however, may be active even at the early stages of information intake, influencing stimulus processing (Herrmann & Knight, 2001). In such a context, P100 may reflect early sensory processing of attended stimuli, while N100 may reflect early attentional orienting toward stimuli (Takeda et al., 2016). This makes early ERP components good candidates for measuring cognitive workload along with the traditionally used endogenous (P300) component. Details on how different ERP components change with cognitive workload variations are provided in **Chapter 3**.

2.3 Summary

The cognitive workload was defined by the theory that the human brain has limited resources to attend to a particular task. The cognitive workload of a task is different from absolute task difficulty and cannot be measured directly. In the literature, there were numerous methods to evaluate cognitive workload, and the value of each method depends on the Situation. Behavioral and subjective methods were less intrusive, but they were not sensitive to cognitive workload changes during the task's performance. Physiological methods and especially neurophysiological methods were the most sensitive to changes in cognitive workload. Some neurophysiological methods, such as PET and fMRI methods were invasive and expensive to implement. Therefore, the most suited neurophysiological methods for rehabilitation were EEG-based cognitive workload evaluation methods. These EEG-based methods were highlighted as safe, easy-to-use, and non-invasive measures that can evaluate cognitive workload changes during the task. Overall, this background review of the literature supported the notion that cognitive workload evaluation methods best suited as an objective method must have low intrusion, high sensitivity to measure changes in cognitive workload during the task, high diagnostic power to differentiate the sources of cognitive workload.

Based on these selection criteria, EEG-based methods were highlighted as best suited to evaluate cognitive workload during rehabilitation. There were two types of EEG-based method that have been used in the literature to evaluate cognitive workload. The frequency-based methods lack temporal resolution and are prone to noise artefacts whereas ERP-based methods were highlighted as robust with high temporal resolutions.

Therefore, ERP-based methods to evaluate cognitive workload were reviewed in detail in **Chapter 3**.

Chapter 3. Narrative synthesis

3.1 Prologue

A scoping review was completed to clarify concepts, identify gaps in ERP literature and see where ERP-based methods to evaluate cognitive workload stands in the literature (Munn et al., 2018). This chapter emphasizes the importance of an effective cognitive workload evaluation method in real-life activities. It then highlights the robustness of a neurophysiological EEG/ERP based cognitive workload evaluation method and its variants. This chapter compares both the single-task and dual-task variants of ERP-based methods and address the following research objective:

- To conduct an extensive review to investigate:
    d. The EEG/ERP based methods to evaluate cognitive workload.
    e. The ERP components best correlated to cognitive workload using single-task ERP paradigms.
    f. The parameters of single-task ERP-based cognitive workload evaluation methods which can affect the evaluation criteria of these methods.

According to the review paper, literature was reviewed up to March 30, 2019. Two literature searches were then conducted (October 11, 2021, and April 1, 2022), which utilized similar inclusion criteria. . This narrative synthesis has been published in a peer-reviewed journal, and it is presented here with no modifications in the content. Few minor formatting modifications are made to facilitate reading (Ghani et al., 2020a).

Start of published manuscript 1.

ERP based measures of cognitive workload: A review.

Ghani, U., Signal, N., Niazi, I.K., Taylor, D., 2020. ERP based measures of cognitive workload: A review. Neuroscience and biobehavioral reviews 118, 18-26.

Keywords: Electroencephalography (EEG), Event-related potentials (ERPs), Cognitive workload, Auditory stimulus, and Cognitive task

3.2 Abstract

This review appraises electroencephalograph (EEG) approaches to cognitive workload evaluation, focussing on the measurement of event-related potentials (ERPs) in single task paradigms. A systematic search was undertaken, studies were included if they used a single task paradigm with an auditory stimulus combined with ERP measures from EEG to evaluate cognitive workload in healthy adults. Nineteen articles met the inclusion criteria. There was a change in the amplitude of ERP components with an increase in cognitive difficulty. However, this change was dependent on the features of the task and stimuli. This review emphasizes the importance of stimulus and task selection in single task paradigms to evaluate cognitive workload. This review also synthesizes important concepts regarding ERPs in single task paradigms such as the effect of primary task selection on specific ERP components.

3.3 Introduction

Human performance is highly dependent on the effective and efficient allocation of brain resources during demanding tasks such as piloting an aircraft, driving a car, or other multifaceted tasks (Carryl, 2012). As the demand of a task increases so does the utilization of brain resources, and this utilization of brain resources can be termed *cognitive workload* (Carryl, 2012). As cognitive workload increases for a particular task, available brain resources for secondary tasks decrease. If the brain resources are depleted below a certain threshold, the cognitive processing of further tasks can be delayed or impeded (Carryl, 2012). Thus, understanding how brain resources are allocated during tasks is critical, and this understanding is based on having an objective and accurate measure of cognitive workload. An accurate measure of cognitive workload is necessary to assess how different task conditions affect cognitive workload and provides a gauge to determine how well learned a given task is. This may afford the opportunity to enhance user-task interaction by varying the task demands according to one's cognitive state (Dyke et al., 2015a).

The concept of cognitive workload stems from earlier work on the theories of attention, in particular the limited capacity theory and the multiple resource theory (MRT) (Basil, 2012; Moray, 1967; Wickens et al., 1984). Central to these theories is the idea that humans are limited in the amount of information they can process at any given time. This idea was verified by work examining the cognitive psychology of attention (Broadbent, 1958; Moray, 1967). In an article by McLeod (2007) humans are termed as information processors who can process limited information at a time and suggested that the information made available is processed by a series of processing systems modulated by attention. Later Luck and Kappenman (2011) refer to attention as a set of processes that control the flow of information through the nervous system. These studies verified that attention modulates cognitive systems (e.g., perceptual systems, memory systems, response systems) to facilitate information flow through central nervous system. In a study by Kahneman (1973), the term attention is used synonymously with cognitive workload. People direct, exert, and invest attention that changes according to the demands of a task. Recently, electroencephalography (EEG) and more specifically event-related potentials (ERPs) have been used extensively to understand the relationship between cognitive workload, attention, and information flow through different cognitive systems.

Event-related potentials (ERPs) are electrical potentials in the electroencephalogram (EEG) that are linked to specific events. ERPs are obtained by the process highlighted in **Figure 3.1(A, B, and C)**. **Figure 3.1A** shows an EEG waveform with marked events (simple auditory tones) and the windows that represent the brain activity in response to these events. This specific activity is different from the rest of the EEG, and averaging EEG across multiple channels will enhance the task related activity while minimizing or cancelling unwanted activity (Luck, 2005). **Figure 3.1B** shows the averaged data from all the event windows, which forms an ERP waveform, highlighted as a solid black line. As shown in **Figure 3.1C**, the averaged ERP waveform is divided into different components based on latency from the stimulus onset. These ERP components are generally named according to the direction of their deflection (P for positive and N for negative) and then either their ordinal position or averaged expected latency (Luck, 2005). For example, the first large negative deflection with an expected latency of 100ms is termed the N100, the first positive deflection with an expected latency of 200ms is termed the P200 and so on.

These ERP components provide temporal information about attentional processes. They highlight neural resources and stages of stimulus/information processing. Each information processing stage requires multiple attentional resources (perceptual, cognitive, or storage) from a limited attentional reserve (Solís-Marcos & Kircher, 2019).

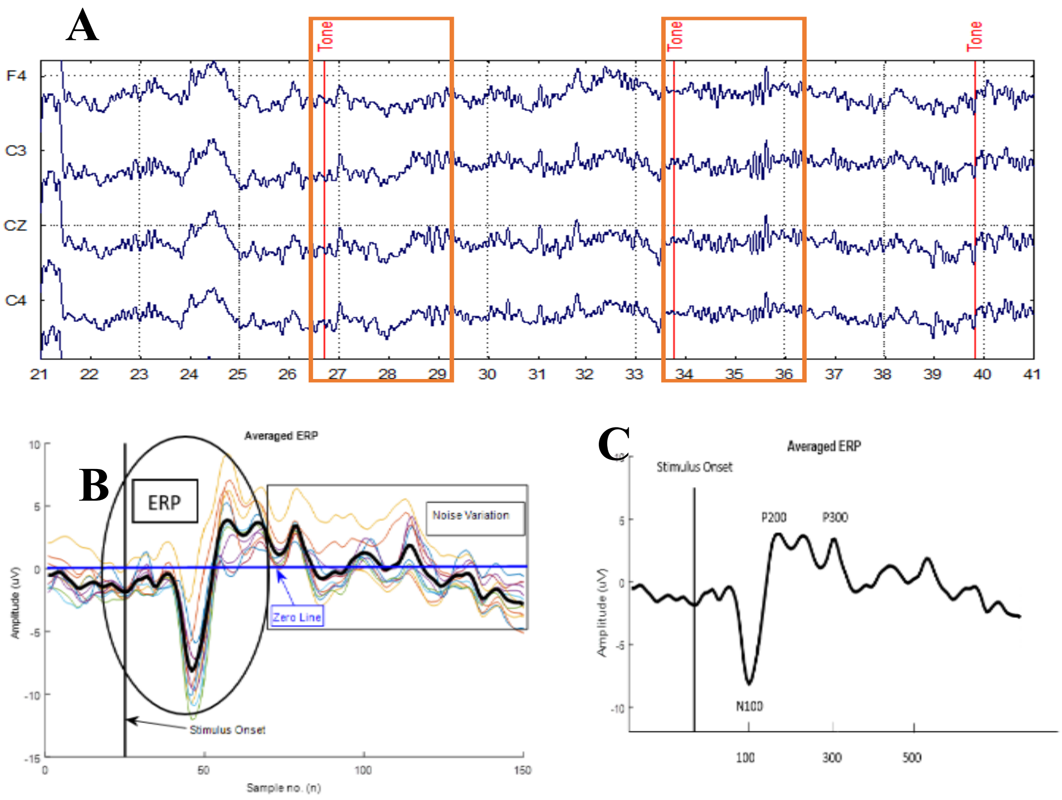

Figure 3.1 (A) shows a typical EEG signal with marked events (tones) and event windows. (B) shows the data from all event windows and averaged ERP waveform. (C) shows the ERP waveform with latency-based components (N100, P200, and P300)

According to multiple resource theory (MRT), this attentional reserve can be divided into multiple small reservoirs for each type of resource (Basil, 2012). These resources are controlled by the central executive or working memory (SanMiguel et al., 2008). The working memory provides an interface between perception, long-term memory, and action. Also, it controls the amount of attention allocated to the task and the stimulus in ERP paradigms (Luck & Kappenman, 2011). Based on the stage of information processing, the ERP components can be divided into perceptual (e.g., N100), cognitive (e.g., P300), and response (e.g., lateralized readiness potential (LRP)) (Sokhadze et al., 2017). Therefore, each ERP component perceptual or cognitive, tap into the reservoir of required resources. The amplitude of these ERP components changes with the amount of attentional resources in the attentional reservoir. These changes in the amplitude of

ERP components are used to evaluate cognitive workload. In this review, ERPs, and their utilization to evaluate cognitive workload will be discussed.

These ERP components can be further categorized based on the stimulus processing. Early ERP components peaking with in first 100ms are termed as exogenous as they depend largely on the physical parameters of the stimulus (Sur & Sinha, 2009a). In contrast, later ERP components (after 100ms) are termed as endogenous as they depend on the evaluation and processing of a stimulus (Sur & Sinha, 2009a). Generally, the early ERP components (N100, N200, or P200) are usually related to attention selection mechanisms, while later ERP components (P300 or later) deal with interpretation or categorization of the stimuli. The N100 reflects early orienting attention towards the stimuli. The N200 is an endogenous component that deals with conflict detection and stimulus processing (Sokhadze et al., 2017). The P200 reflects attention and discrimination processes as well as task difficulty related variables (Conley et al., 1999). The P300 is the most studied endogenous ERP component, which deals with categorization of the stimulus (Gentili et al., 2014). All the aforementioned ERP components show a response to attentional demands and have been used to evaluate cognitive workload. The generation of each ERP component depends on the task and the stimuli used. ERP based methods that evaluate cognitive workload can be divided into two different paradigms based on the task that participants perform.

In dual-task paradigms, the cognitive difficulty is manipulated using two distinct tasks performed at the same time. The main task is termed the primary task, and the other task is termed secondary. The difficulty of the primary task is manipulated using the secondary task. For example, Ullsperger et al. (2001) used a dual-task paradigm to evaluate cognitive workload in which monitoring a gauge was the primary task and to vary the difficulty of this task a secondary arithmetic task was used. Dual-task paradigms require a lot of brain resources, the introduction of a secondary task induces additional cognitive workload in intractable ways (Miller et al., 2011). This secondary task can distract participants from the primary task with the result that it becomes hard to provide an exact measure of the cognitive workload associated with the primary task (Allison & Polich, 2008). The dual task paradigm can fatigue the participants quickly as they perform two tasks at the same time (Allison & Polich, 2008).

In single task paradigms, there is only one task, which, of course, is primary. The advantage of focusing on single task paradigms is that they can provide a clearer cognitive workload estimation as compared to dual-task paradigms (Deeny et al., 2014). In single task paradigms, participants perform a primary task, and they are probed with different stimuli which can utilize any sensory modality, for example, these stimuli can be tactile, auditory, or visual. For evaluating cognitive workload, auditory stimuli are considered more robust (Dyke et al., 2015a). Irrespective of the sensory modality, these stimuli generate specific ERP events in EEG. There are three different methods used to provide these stimuli **1)** oddball, **2)** single stimulus, and **3)** three stimuli. In an oddball paradigm, the participant is provided with multiple stimuli, among which only one is the target stimulus. In single stimulus paradigms, only a single targeted stimulus is provided. In three stimuli paradigms, three distinct stimuli (standard, target, and distractor) are presented to the participants. It is similar to an oddball paradigm with the addition of a distractor stimulus inserted in the sequence of target and standard stimuli.

In recent literature, these single task paradigms either used a separate primary motor or cognitive task with auditory stimuli or used an auditory stimulus discrimination task where different auditory stimuli were presented. In an experimental setup where a separate cognitive or motor task was used, as highlighted in **Figure 3.2A**, a probing stimulus was provided during the task. This probing stimulus generated an ERP, which was then used to evaluate the cognitive workload associated with the task. In another scenario where only stimuli were presented is shown in **Figure 3.2B**, the task is to discriminate the different stimuli, and no separate task is presented to the participants.

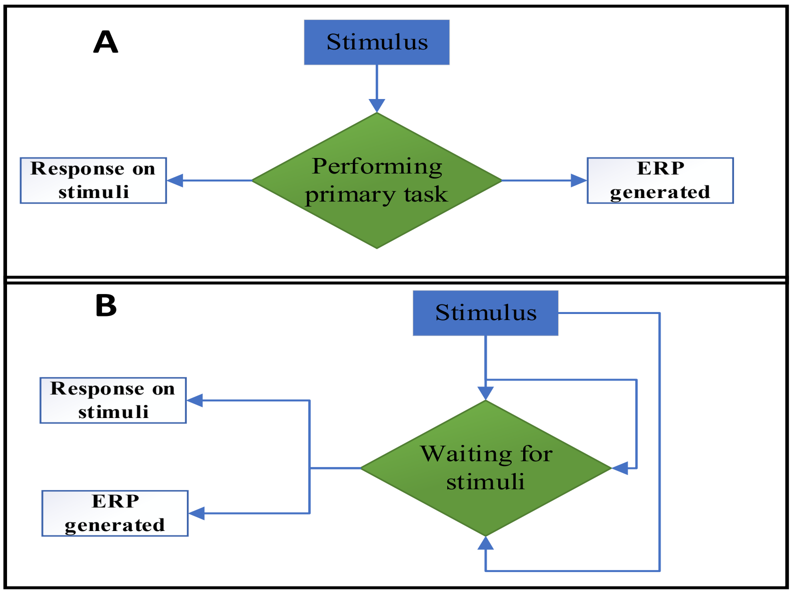

Figure 3.2 (A) Shows a setup where a separate primary task (motor or cognitive) was presented. (B) shows a discrimination task approach.

Many variations of single task paradigms with an auditory stimulus have been proposed and there is a large diversity across these paradigms based on the presentation of the task and the type of auditory stimuli. This review evaluates the efficacy of these single task paradigms with auditory stimuli to evaluate cognitive workload in healthy adults.

Table 3.1 Abbreviations

Abbreviations	
EEG	Electroencephalogram
ERP	Event-related potentials
CNS	Central Nervous System
P100	Positive peak at 100ms
P200	Positive peak at 200ms
P300	Positive peak at 300ms
N100	Negative peak at 100ms
N200	Negative peak at 100ms
MMN	Miss-Match Negativity
P3a	First subcomponent of P300
P3b	Second subcomponent of P300
N2a	First subcomponent of N200
N2b	Second subcomponent of N200

It also provides a comprehensive synthesis of concepts regarding ERPs and their utilization in cognitive workload evaluation. We examined the ERP and cognitive workload literature and synthesized studies of single task paradigms to report how they were used, what the outcomes were, and highlight the strengths and weaknesses of measuring cognitive workload using single task paradigms. The abbreviations used are provided in **Table 3.1**.

3.4 Method

3.4.1 Identification of relevant studies

Studies were identified from the following electronic databases based on key search terms for all available years, MEDLINE via (PubMed, Ovid, EBSCO, and Web of Science), ScienceDirect, and Scopus. The search strategy included the following key search terms: EEG, electroencephalogram, mental workload, cognitive workload, task difficulty, ERP, Event-related potentials, healthy, auditory, tones, sounds. The reference lists of included studies were also searched to identify further studies. The final database search was completed on March 30, 2019.

3.4.2 Inclusion and exclusion criteria

Studies were included if they met the following criteria: included healthy participants above the age of 18 years, evaluated cognitive workload using single task paradigms, measured ERP components, used auditory stimuli, and appeared in English-language journals. Studies using any experimental setup within a single task paradigm to look at the effect of parameters such as age, inter-stimulus-distance (ISD), and working memory (WM) on cognitive workload were also included in this review.

Studies were excluded if they were reviews, books, theses, conference papers, letters, animal based, language-specific studies, and speech recognition studies.

3.4.3 Selection of studies

After removing the duplicates, the first author (UG) reviewed the titles and abstracts of all the studies. If a decision to include an article could not be made based on the title and abstract review, the full text was reviewed.

3.4.4 Data Extraction

The following information was extracted: study characteristics, participant information, experimental setup, outcome variables, and key findings.

3.5 Results

The electronic search retrieved 352 studies, and ten studies were added manually from hand searching the reference lists of the retrieved studies. After the removal of duplicates, a total of 254 studies remained. Title and abstract review excluded 224 studies that did not meet the eligibility criteria. After exclusion based on the title and abstract, 30 articles were retained for full-text review. Following the full-text review, 11 articles were excluded from the review based on the reasons highlighted in the PRISMA flow diagram shown in **Figure 3.3**.

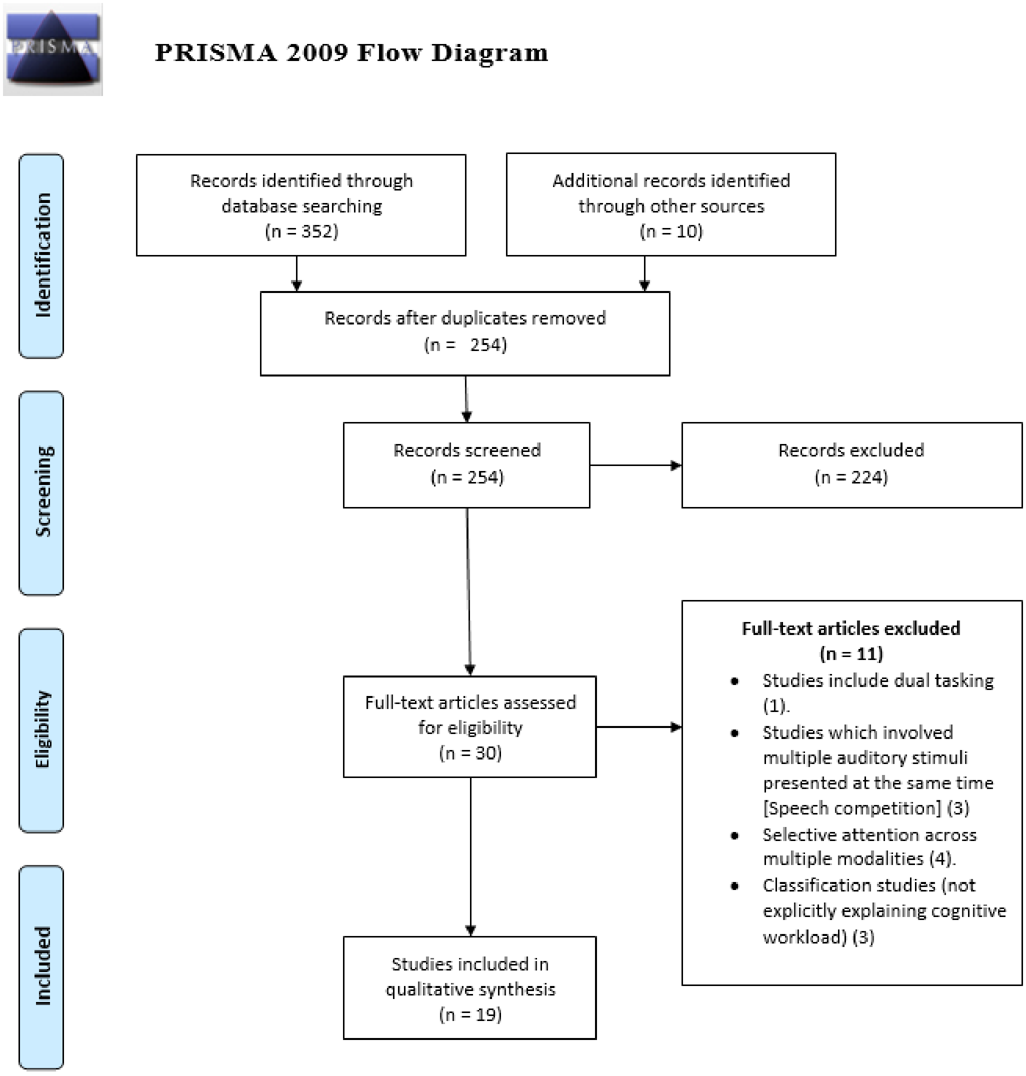

Figure 3.3 PRISMA Flowgraph.

A total of 19 studies met the inclusion criteria and were included in the review. No additional studies met the inclusion criteria after searching the reference lists of included studies. The included studies involved a total of 359 participants with the mean age between 19 and 68 years. Only one study had participants above the age of 40 years (Gaal et al., 2007). There were two major variations of the task within the single task paradigms. The single task was either an auditory stimulus discrimination task (n = 9) (Berti & Schroger, 2003; Combs & Polich, 2006; Frank et al., 2012; Gaal et al., 2007; Goodin et al., 1983; Horat et al., 2016; Muller-Gass et al., 2007; Novak et al., 1990; Polich, 1987) or it was a separate cognitive or motor task with an auditory stimulus (n = 10) (Allison & Polich, 2008; Causse et al., 2015; Deeny et al., 2014; Kramer et al., 1995; Miller et al., 2011; Muller-Gass & Schroger, 2007; Sculthorpe et al., 2008; Suzuki et al., 2005; Takeda et al., 2016).

3.5.1 Manipulations and outcomes

Included studies looked at the amplitude and latency of multiple ERP components as a measure of cognitive workload. Two studies looked only at early ERP components (N100, N200, and MMN) (Sculthorpe et al., 2008; Takeda et al., 2016). Ten studies looked at both early (N100, N200, and MMN) and late ERP components (P300, P3a, P3b, and LPP) to evaluate cognitive workload (Allison & Polich, 2008; Berti & Schroger, 2003; Deeny et al., 2014; Goodin et al., 1983; Horat et al., 2016; Kramer et al., 1995; Miller et al., 2011; Muller-Gass et al., 2007; Muller-Gass & Schroger, 2007; Novak et al., 1990). Seven studies looked only at P300 or subcomponents of the P300 (P3a and P3b) (Causse et al., 2015; Combs & Polich, 2006; Dyke et al., 2015a; Frank et al., 2012; Gaal et al., 2007; Polich, 1987; Suzuki et al., 2005). The studies that looked at the P300 component can be divided into two categories 1) studies investigated the whole P300 waveform (Allison & Polich, 2008; Deeny et al., 2014; Goodin et al., 1983; Kramer et al., 1995; Miller et al., 2011; Polich, 1987) 2) studies which divided the P300 component into two subcomponents P3a and P3b (Berti & Schroger, 2003; Causse et al., 2015; Combs & Polich, 2006; Dyke et al., 2015a; Frank et al., 2012; Gaal et al., 2007; Horat et al., 2016; Muller-Gass et al., 2007; Muller-Gass & Schroger, 2007;

Novak et al., 1990; Suzuki et al., 2005). Study characteristics and key findings are provided in Error! Reference source not found..

3.5.2 N100 component

The N100 component (90−200ms post-stimulus) is a short latency ERP component mostly generated by the frontal cortex (Sur & Sinha, 2009a). A study by Näätänen and Michie (1979) suggested that N100 reflects early stages of attention orienting and can be used in attention- related studies. In single task paradigms, the N100 was first investigated by Kramer et al. (1995). Findings from this study reported that the amplitude of the N100 decreased with an increase in cognitive workload. A similar decrease in N100 amplitude was reported in all three studies that used a separate primary task with auditory stimuli (Allison & Polich, 2008; Miller et al., 2011; Takeda et al., 2016). Only one study (Muller-Gass & Schroger, 2007) reported an increase in the N100 component with an increase in task difficulty. However, in this study, an auditory discrimination task was used as the primary task; as the auditory discrimination became more difficult, more attention was given to the auditory stimulus. This investment of attention can be seen as an increase in the amplitude of N100.

3.5.3 N200 Component

The N200 component (180−320ms post-stimulus) is a negative ERP component located over centro-parietal scalp locations (Sur & Sinha, 2009a). Four studies looked at the N200 component as a single component and reported a decrease in the amplitude of the N200 component with an increase in cognitive workload (Allison & Polich, 2008; Goodin et al., 1983; Kramer et al., 1995; Novak et al., 1990). Goodin et al. (1983) compared the latency change of the N200 component with variations in cognitive workload and reported an increase in the latency of N200 as cognitive workload increased. There were six studies that examined the subcomponent of N200 known as mismatch negativity (MMN) (Berti & Schroger, 2003; Kramer et al., 1995; Muller-Gass et al., 2007; Muller-Gass & Schroger, 2007; Novak et al., 1990; Sculthorpe et al., 2008). The MMN corresponds to a change in stimulus. All studies except Kramer et al. (1995) reported that the amplitude of MMN did not change with task difficulty and suggested that the MMN is an attention independent component. One of these studies by Sculthorpe et al. (2008) looked explicitly at MMN in a single-task paradigm using different inter-stimulus intervals (ISIs) and reported that the amplitude of MMN did not vary due to task difficulty.

3.5.4 P200 component

The P200 component (100−250ms post-stimulus) is a positive ERP component located over centro-frontal scalp locations (Sur & Sinha, 2009a). Six studies looked at the amplitude of P200 in single task paradigms and consistently across all six studies the amplitude of P200 decreased with an increase in cognitive workload (Allison & Polich, 2008; Deeny et al., 2014; Horat et al., 2016; Kramer et al., 1995; Miller et al., 2011; Takeda et al., 2016).

3.5.5 P300 component

The P300 component (250−500ms post-stimulus) is the most studied positive endogenous component located at fronto-central (p3a) or centro-parietal (p3b) depending on the novelty of the stimulus (Sokhadze et al., 2017). The P300 has been used extensively to evaluate cognitive workload in single task paradigms. In studies included in this review six looked at the amplitude of the P300 component to evaluate cognitive workload. They all reported a decrease in the amplitude of P300 with an increase in cognitive workload (Allison & Polich, 2008; Deeny et al., 2014; Goodin et al., 1983; Miller et al., 2011; Polich, 1987). The P300 was reported to be dependent on the type of auditory stimuli. Kramer et al. (1995) used a task-irrelevant auditory stimulus and reported that the P300 was not generated because no attention was given to this task-irrelevant auditory stimulus. In this experiment, earlier ERP components such as N100 and N200 did show changes (see section 3.1.1 and 3.1.2). Miller et al. (2011) and Deeny et al. (2014) investigated the effect of different types of auditory stimuli on the P300 component and reported that novel sounds captured more attention and generated a large P300 component compared to simple auditory tones. This finding has been replicated across three other studies (Combs & Polich, 2006; Dyke et al., 2015a; Frank et al., 2012).

Eleven studies looked at the utility of subcomponents of the P300 (P3a and P3b) in evaluating cognitive workload (Berti & Schroger, 2003; Causse et al., 2015; Combs & Polich, 2006; Dyke et al., 2015a; Frank et al., 2012; Gaal et al., 2007; Horat et al., 2016; Muller-Gass et al., 2007; Muller-Gass & Schroger, 2007; Novak et al., 1990; Suzuki et al., 2005). The P3a component had a fronto-central distribution and was evident only in the presence of a distractor stimulus. The amplitude of the P3a represented the amount of attention given to the distractor stimulus (Dyke et al., 2015a). Studies that looked at the P3a subcomponent as a measure of cognitive workload using a single task paradigm reported contradictory findings; 1) that the P3a decreased with an increase in cognitive workload (Berti & Schroger, 2003; Dyke et al., 2015a; Horat et al., 2016), 2) that the P3a increased with an increase in cognitive workload (Combs & Polich, 2006; Muller-Gass & Schroger, 2007), or 3) that the P3a was not affected by an increase in cognitive workload (Muller-Gass et al., 2007).

The P3b subcomponent is thought to reflect parietal functions as- sociated with high level processes such as the categorization of stimuli and updating of working memory (Causse et al., 2015). It is well established that the P3b component represents stimulus classification, and its amplitude decreases with an increase in cognitive workload (Causse et al., 2015; Combs & Polich, 2006; Frank et al., 2012; Novak et al., 1990). It has also been reported that the latency of the P3b represents the speed of classification of stimuli and increases with an increase in cognitive workload (Combs & Polich, 2006; Horat et al., 2016). Gaal et al. (2007) looked at the relationship of latency of the P3b and age. Their findings suggested that the latency of the P3b increased with increasing cognitive workload, but this pattern changes with age. They reported that the latency of the P3b increased linearly with age in easy task conditions. In contrast, an accelerated increase in the latency was seen in difficult task conditions. Irrespective of the pattern of the change in amplitude and latency, this change was in the same direction for P3b in all the literature.

Table 3.2 Characteristics of included studies

Study	Participants	Task setup	Stimuli	Target ERPs	Main Findings
(Goodin et al., 1983)	14 Healthy Age: 31.0±7.0 years	Tone Discrimination	Oddball paradigm Stimulus type: Simple tones	P_{165}, N_{200} , P_{300}	Latency of P_{165}, N_{200} and P_{300} increased with increasing task difficulty. Amplitude of P_{165} increased with increased task difficulty
(Polich, 1987)	16 Healthy Age: 21.2±2.6 years	Tone Discrimination	Oddball paradigm Stimulus type: Simple tones	P_{300}	Amplitude of P_{300} decreased and latency increased with increased task difficulty. No interaction of task difficulty and ISI. Amplitude and latency of P_{300} was influenced by the combination of task, probability of stimulus presentation, and ISI.
(Kramer et al., 1995)	10 Healthy navy radar operators Age: 28.5± 5.5 years	One Primary Task Radar Monitoring	Oddball paradigm Stimulus type: Simple tones	N_{100}, N_{200}, P_{200} , MMN and P_{300}	Amplitude of $N_{100}, N_{200}, P_{200}$ and MMN decreased with increased cognitive workload. P_{300} was not generated by task-irrelevant ignored auditory probes. Successfully evaluated cognitive workload using ignored auditory probes.

Table 2: Characteristics of included studies (Continued)

Study	Participants	Task setup	Stimuli	Target ERPs	Main Findings
(Combs & Polich, 2006)	16 Healthy Age: 19.2±1 year	Tone Discrimination	3-stimulus paradigm Stimulus type: Simple tones White noise Novel sounds	P_{3a} and P_{3b}	P3a amplitude was sensitive to the distractor (high for white noise) P3a amplitude increased with increased discrimination difficulty. Difficult tasks engaged more attentional resources so larger P3a (large attentional capture) Increased P3a affected P3b amplitude and increased its latency. White noise minimized habituation. P3b target amplitude was unaffected by distractor type, and amplitude decreased, and latency increased with task difficulty
(Gaal et al., 2007)	55 Healthy Age: 19 years to 68 years	Tone Discrimination	3-stimulus paradigm Stimulus type: Simple tones Novel sounds	P_{3a} and P_{3b}	P3b latency increased linearly with age for an easy task. Accelerated latency increase of P3b and P3a for the difficult condition (quadratic). P3a amplitude decreased, and latency increased with age. P3b amplitude decreased with increased demand.

Table 2: Characteristics of included studies (Continued)

Study	Participants	Task setup	Stimuli	Target ERPs	Main Findings
(Berti & Schroger, 2003)	10 Healthy Age: 22.5±3.5 years	Tone Discrimination	Oddball paradigm Stimulus type: Simple tones	P_{3a}, N_{100} and MMN	MMN was not modulated by the task difficulty. P3a reduced with increased task difficulty. N1 amplitude was decreased in high workload. Less attention to stimulus was given under high workload conditions.
(Suzuki et al., 2005)	12 Healthy Age: 22.5±2.5 years	One primary task Video Monitoring	3-stimulus paradigm Stimulus type: Simple tones	P_{300}, P_{3a}, and P_{3b}	The amplitude of both target and deviant P_{300} decreased as video became more interesting. The P_{300} in response to deviant tones had shorter peak latency then target tones. Target tones generated P3b while deviant tones generated P3a. P3a was vulnerable to habituation. Amplitude reduction in P3a was larger. P3a was more sensitive to resource availability then P3b. Deviant response (P3a) decreased with time because of habituation.

Table 2: Characteristics of included studies (Continued)

Study	Participants	Task setup	Stimuli	Target ERPs	Main Findings
(Muller-Gass et al., 2007)	10 Healthy Age: 21.8±1.5 years	One Primary task Visual tracking task	3-stimulus paradigm Stimulus type: Simple tones	P_{3a} and MMN	P3a did not require central capacity, and it represented a strongly automatic process. The amplitude of P3a was not affected by the task difficulty. Reorientation negativity (RON) decreased with task difficulty. MMN is not affected by visual demands. Nature of P3a is dependent on generating conditions
(Muller-Gass & Schroger, 2007)	13 Healthy Age: 22.5±3.5 years	Tone Discrimination	Oddball paradigm Stimulus type: Simple tones	N_{100}, P_{3a} and MMN	N1 amplitude enhanced with stimulus processing demands. P3b latency indexed stimulus classification speed MMN was not affected by task demands. P3b amplitude decreased, and latency increased in high workload conditions. The amplitude of P3a increased in high workload conditions
(Sculthorpe et al., 2008)	14 Healthy Age:21.5±3.5 years	One Primary task Multiple objects tracking	Oddball paradigm Stimulus type: Simple tones	MMN	Stimulus separation did effect MMN (less separation →less amplitude) MMN was automatic and was not affected by the difficulty of visual tracking task.

Table 2: Characteristics of included studies (Continued)

Study	Participants	Primary Task setup	Stimuli	Target ERPs	Main Findings
(Deeny et al., 2014)	18 Healthy Age: 29.5±8.5 years	One Primary task Prosthesis Control	Single stimulus Stimulus type: Novel sounds	P_{200}, P_{300}, and LPP	The amplitude of P200, P300, and LPP was inversely related to cognitive workload.
(Causse et al., 2015)	15 Healthy Age: 24.6±1.86 years	One Primary Task Piloting	Single stimulus Stimulus type: Novel sounds	P_{3b}	The amplitude of P3b decreased with an increase in cognitive workload. P3b reflected the depletion of cognitive resources
(Dyke et al., 2015a)	80 Healthy Age: 22.5±3.7 years	One Primary Task Videogame	Single stimulus Stimulus type: Novel simple sounds Novel complex sounds	P_{3a}	P3a component decreased monotonically as a function of cognitive workload. Complex stimuli were significantly more effective in indexing cognitive workload.

Table 2: Characteristics of included studies (Continued)

Study	Participants	Task setup	Stimuli	Target ERPs	Main Findings
(Allison & Polich, 2008)	14 Healthy frequent gamers Age: 23.5±5.1 years	One Primary task First person shooter game	Single stimulus paradigm Stimulus type: Simple tones	N_{100}, N_{200}, P_{200}, P_{300}, SW1, and SW2	N100 amplitude decreased with an increase in cognitive workload, and it was more pronounced in ignored condition. N200 amplitude diminished as difficulty increased in count condition. P300 amplitude decreased with an increase in task difficulty. Early slow wave component (Sw1) decreased in amplitude with an increase in cognitive workload. SW2 was not affected.
(Miller et al., 2011)	20 Healthy Age: 24.4±4.1 years	One Primary Task Playing Tetris	Oddball paradigm Stimulus type: Simple tones Novel sounds	N_{100}, P_{200}, and P_{300}, LPP	The amplitude of all the ERP components decreased with an increase in cognitive workload. P300 and LPP were most sensitive to the changes in task difficulty. N100 and P200 amplitude reduction meant less resource allocation to a stimulus.
(Frank et al., 2012)	16 Healthy Age: 20.1±1.9 years	Tone Discriminat ion	3-stimulus paradigm Stimulus type: Simple tones White noise Novel sounds	P_{3a} and P_{3b}	P3a was larger with shorter latency for white noise, and it was not affected by difficulty levels. P3b was not affected by distractor type, and its amplitude decreased with an increase in cognitive workload. Both distractor salience and discrimination difficulty determine amplitude topography.

Table 2: Characteristics of included studies (Continued)

Study	Participants	Primary Task setup	Stimuli	Target ERPs	Main Findings
(Takeda et al., 2016)	17 Healthy Age: 27.5±8.5 years	One Primary task Driving Simulator	3-stimulus paradigm Stimulus type: Simple tones	N_{100} and P_{200}	The feeling of pleasure and task difficulty both consumed attentional resources but did not covary with each other. N100 amplitude decreased with an increase in pleasure. P200 amplitude decreased with an increase in task difficulty
(Horat et al., 2016)	16 Healthy Age: 27.5±4.3 years	Tone Discrimination	Oddball paradigm Stimulus type: Simple tones	P_{3a}, P_{200} and P_{3b}	P200 amplitude was inversely proportional to the task difficulty. P3a and P3b latency increased with task difficulty. The amplitude of P3a and P3b decreased with an increase in the task difficulty.

3.6 Discussion

People have limited attentional capacity, and, at a basic level, this consists of two components: the attentional capacity used in the task itself (cognitive workload) and additional capacity that is kept in reserve (attentional reserve). Based on ERP measures Jaquess et al. (2017) and Gentili et al. (2014) demonstrated that cognitive workload was inversely propotional to attentional reserve. ERP measures of attentional capacity have two parameters 1) the primary task which participants perform and 2) the stimuli to generate the ERP components. The amplitude of these ERP components change with the amount of attention given to the primary task or the stimuli, and this allocation of attention depends on the attentional reserve (Gentili et al., 2018). Although a reduction in the amplitude of the ERP components represents a reduction of attentional reserve, this reduction can also be used to evaluate cognitive workload associated with a primary task (Causse et al., 2015; Deeny et al., 2014; Horat et al., 2016; Miller et al., 2011). In this review, we focused on studies which used a reduction in the amplitude of ERP components to evaluate cognitive workload of a primary task using single task paradigms.

Every task has specific demands and occupies attention based on these demands (Solís-Marcos & Kircher, 2019). This attention then modulates other cognitive systems (e.g., perceptual systems, memory systems, response systems), and according to the multiple resource theory (MRT), every cognitive system has limited resources (Wickens, 1991). Based on the type of task, we can infer the resources demanded by the task. For example, two types of tasks were discussed in the included studies. 1) a separate motor or cognitive task with auditory stimuli, and 2) an auditory stimulus discrimination task. In the first type of task, more cognitive resources were occupied. In the second type of task where an auditory stimulus discrimination task is used, more perceptual resources were occupied. Both types of tasks and their effect on different ERP components are discussed in this review.

The ERP components also give information on cognitive systems. Early and more frontal ERP components (N100 or N200) are related to perceptual processing (Kramer et al., 1983), while later and more parietal ERP components (P300 or later) are related to cognitive pro- cessing (Solís-Marcos & Kircher, 2019). In this review, the amplitude and latency of both early (N100, N200, and P200) and late (P300, P3a, and P3b) ERP components were looked at to evaluate cognitive work- load in single task paradigms.

3.6.1 Effect of cognitive workload on individual ERP components

The N100 is elicited during stimulus identification and is linked to attentional selection processes and the allocation of perceptual resources (Solís-Marcos & Kircher, 2019). So, if a separate cognitive or motor task is presented with auditory stimuli, then the amplitude of the N100 *decreases* with an increase in cognitive workload. This is because an increase in the difficulty of cognitive or motor tasks occupies more cognitive resources resulting in a decrease in available attention for perceptual processing. On the other hand, in an auditory stimulus discrimination task, the amplitude of the N100 *increases* with an increase in cognitive workload. This is due to the nature of the task, as the discrimination task becomes difficult, more perceptual resources are occupied. In general, the N100 is dependent on early attentional resources (perceptual or cognitive) and can be used to evaluate cognitive workload at an early information processing stage.

The N200 is divided into two sub-components based on topographic differences. The N2a has fronto-central topography compared to the centro-parietal of N2b (or traditional N200). The N2a component is also known as mismatch negativity (MMN) and represents a change in stimulus. The amplitude of MMN does not vary with cognitive workload and is considered an automatic response to a change in stimulus (Muller-Gass & Schroger, 2007). The latency of MMN increases with an increase in cognitive workload in single task paradigms (Sculthorpe et al., 2008). It can be used in ERP studies where a change in stimulus presentation affects the amplitude and generation of the specific ERP components required for cognitive workload evaluation. For example, a novel distractor stimulus generates a large MMN, which affects the generation of later ERP components. The N2b component is associated with the categorization of stimuli and attention orienting to the stimuli. In general, the amplitude of N2b is dependent on processing demands and these demands require cognitive resources. Therefore, the amplitude of N2b can be used as useful measure of cognitive workload when a separate motor or cognitive task with auditory stimuli is presented to the participants.

The P300 is the most widely used ERP component to evaluate cognitive workload. It is associated with central processes such as the categorization of distinct stimuli and the allocation of cognitive resources (Solís-Marcos & Kircher, 2019). The amplitude of the P300 component represents the amount of resources in the attentional reserve (Kok, 2001). For example, a higher amplitude of the P300 means more resources available in the attentional reserve. In a study by Rietschel et al. (2014), the amplitude of the P300 was used to measure motor skill learning. In this study, as skill increased it required fewer attentional resources leaving a large attentional reserve, which was associated with an increase in the amplitude of the P300 component. These studies show that the amplitude of the P300 provides a good measure of attentional reserve. As stated earlier cognitive workload and attentional reserve are inversely related, therefore, the amplitude of the P300 can be used in the evaluation of cognitive workload. This notion is consistent with numerous studies that show a decrease in the amplitude of the P300 as the cognitive workload increases (Deeny et al., 2014; Gentili et al., 2014; Kramer et al., 1995; Polich, 1987). The latency of the P300 component also shows a direct relationship with cognitive workload (Polich, 1987). For example, as cognitive workload increases the peak latency of the P300 also increases. These findings make the amplitude and latency of the P300 good measures of attentional reserve as well as cognitive workload.

Some authors divide the P300 into two subcomponents, the P3a (also known as novelty P3) and P3b (traditional P300). Both P3a and P3b have distinct topographic distributions and latencies. The P3a has a frontal/central distribution with a small peak latency. In contrast, the P3b has a parietal distribution with a high peak latency. The P3a is generated when a novel stimulus is presented to the participant. If the stimulus is not novel, only the P3b component is generated. This shows that the P3a component may be more directly related to an orienting response than the P3b. In single task paradigms, if an auditory stimulus is novel it captures focal attention and generates a P3a component followed by a P3b component used to update memory. If an auditory stimulus during the task is not novel it only generates a P3b component. This shows that the novelty of the auditory stimulus affects the P3a, not the P3b. Finally, based on the findings, the P3a and the P3b are most likely variants of the same ERP component (P300) that varies in topography based on the novelty of the stimuli.

The amplitude of P3b represents the process of updating working memory. Whenever a stimulus is categorized (novel or not), it updates the working memory. This updation of working memory requires cognitive resources from the attentional reserve, and the amount of resources in attentional reserve depends on cognitive workload. Therefore, the amplitude of the P3b component consistently decreases with an increase in cognitive workload. This consistency makes the P3b one of the most used ERP components for evaluating cognitive workload in single task paradigms.

However, there are variations in findings relating to the amplitude of the P3a component. Three different views regarding the P3a were evident 1) The amplitude of the P3a *decreased* with an increase in cognitive workload, 2) The amplitude of the P3a *increased* with an in- crease in cognitive workload, and 3) the amplitude of the P3a was not *affected* by cognitive workload. These interpretations can be explained based on the task and variation in task demands. Based on these findings, if separate cognitive or motor tasks are presented with an auditory stimulus, and the task difficulty is varied to the extent that it occupies most of the brain resources, then a decline in the amplitude of the P3a component with an increase in cognitive workload is seen. Similarly, in an auditory stimulus discrimination task, if the task is made more difficult, participants pay more attention to all the stimuli, including distractor stimulus, with a resultant increase in the P3a component. Irrespective of the task, if the difficulty is not manipulated up to the extent of occupying most of the attentional resources, the distractor keeps on getting the same attention, and the amplitude of the P3a component remains the same. Therefore, careful selection of the task and manipulation of task demands is required to use the P3a component as a measure of cognitive workload.

3.7 Conclusions

All the studies used robust measures to validate the task difficulty before analysing any ERP components for evaluating cognitive workload. This makes each study, a validating proof of the concept that any of the ERP components (N100, N200, P200, or P300) can be used as objective measures to evaluate cognitive workload in single task paradigms. This review highlights the advantages and disadvantages of different presentations of a task within single task paradigms to evaluate cognitive workload. There is one major issue associated with these single task paradigms, and that is the selection of the task. It becomes challenging to specify difficulty levels of a single task in the absence of a secondary task. According to the literature, the single task should be difficult enough to capture most of the attentional resources, but there is no direct measure of the amount of these attentional resources. This review also synthesizes important concepts regarding ERPs and their utilization in the evaluation of cognitive workload using single task paradigms. For example, if the primary task occupies more cognitive resources, the endogenous ERP components which deal with cognitive processing such as N200, P3b, or P300 will be most affected by the difficulty of the task. Similarly, If the primary occupies more perceptual resources, both the exogenous and endogenous ERP components which deal with perceptual processing such as N100, N200, and P3a will be more affected by the difficulty of the task. Another important aspect of ERP based paradigms is the stimulus used, this review highlights the importance of selecting a robust stimulus to generate reliable ERP components. These ERP components, together with task and stimulus selection within single task paradigms, provide enough evidence to consider these paradigms an effective measure to evaluate cognitive workload. Although enough evidence is provided for the effectiveness of these single task paradigms, there is a need to refine the algorithms being used in these paradigms. Single task paradigms used so far in cognitive workload literature use an averaging based algorithm. This averaging algorithm gives a distinct ERP component out of the noise, but this can mask other patterns that are present in an individual ERP component. These patterns are essential to understand in order to translate this attentional workload measurement technique into real-time scenarios.

3.8 Acknowledgements

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End of the published manuscript

3.9 Objectives identified for further research.

The literature review identified a need for studies that look at the evaluation of cognitive workload using single-task ERP methods in rehabilitation. Currently, there are no studies that examine the use of this method for assessing cognitive workload of rehabilitation tasks. This section highlights the research objectives to address this literature gap.

Efficacy of single-task ERP paradigms: One important objective is to validate the efficacy of single-task ERP paradigms by looking at the effect of factors such as habituation, fatigue, and boredom.

Evaluation of single-task ERP paradigm during rehabilitation-like tasks: A single-task paradigm must first be tested for feasibility in rehabilitation-like tasks before it can be implemented in actual rehabilitation activities.

3.10 Summary

This narrative synthesis of ERP-based paradigms to evaluate cognitive workload highlighted the robustness of single-task ERP-based methods for assessing cognitive workload. Their applicability has been highlighted in various real-life scenarios. Based on the findings, the evaluation criteria of single-task ERP-based cognitive workload evaluation methods varied based on the task and stimuli used. There were two types of tasks outlined in this review, each with separate assessment criteria within a single-task ERP-based paradigm. In a cognitive/motor task with separate stimuli, ERP amplitude decreased as cognitive workload increased, whereas in a stimuli discrimination task, ERP amplitude increased as cognitive workload increased. Furthermore, ERP components in terms of their topographic differences and their relationship to cognitive workload were also explained.

All the included studies used robust measures to validate the actual task difficulty before analyzing any ERP components associated with cognitive workload. This review provided a validating proof of the concept that any of the ERP components (N100, N200, P200, or P300) can be used as objective measures to evaluate cognitive workload in single task ERP paradigms. The P3a which was generated as a result of a novel distractor had contradictory findings which were highlighted in the manuscript and appeared to be the result of the task and stimuli used. Despite this review highlighting the robustness and adaptability of the single-task ERP-based method, the effect of habituation of stimuli was not addressed in the literature. In light of this literature gap, there was a need for a method to validate the efficacy of these single-task ERP-based cognitive workload evaluation criteria by minimizing the effect of habituation.

We re-ran the inclusion criteria on October 11, 2021, and then April 1, 2022, several studies have developed and updated single-task cognitive workload evaluation methods. Xu et al. (2020) worked on the inter-task reliability of ERPs generated by task irrelevant auditory probes as indicators of cognitive workload. They reported that ERPs from task irrelevant auditory probes differentiated between the levels of cognitive workload irrespective of the task. Ortiz et al. (2020) used wireless EEG electrodes to help translate single-task cognitive workload evaluation method in clinics where as Robles et al. (2021) used ERPs to evaluate cognitive workload in dynamic environment (skate-boarding). Tang et al. (2021) provided an updated signal processing technique for ERPs to limit movement and other noise. This highlights the development and focus given to single-task ERP based cognitive workload evaluation methods towards real-time cognitive workload evaluation.

Chapter 4. A novel method to minimize habituation in single-task ERP paradigm to evaluate cognitive workload

4.1 Prologue

This chapter first highlights the benefits of single-task ERP-based cognitive workload evaluation methods over dual-task methods. It then presents a major issue of habituation with single-task ERP based methods (highlighted in the previous chapter) and provides a solution through an experimental study to minimize the effect of habituation. This chapter addresses the following thesis objective:

- To conduct an experimental study to:

    c. Provide a framework to address the limitations of single-task ERP-based method highlighted in the review.

    d. Validate the efficacy of the single-task ERP methods to evaluate cognitive workload.

This experimental study has been published in a peer-reviewed journal, and it is presented here with no modifications in the content. A few minor formatting modifications are made to facilitate reading (Ghani et al., 2020b). The supporting documents associated with this chapter can be found in the **Appendices**. These documents are participant information sheet (Appendix A), advertisement poster for recruitment (Appendix B), ethics approval letter (Appendix C), protocol (Appendix D), and consent form (Appendix E).

Start of published manuscript 2.

A novel approach to validate the efficacy of single task ERP paradigms to measure cognitive workload.

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Keywords: Electroencephalography (EEG), Event-related potentials (ERPs), Cognitive workload, Auditory stimulus, and Cognitive task

4.2 Abstract

The present study examined the utility of a single-task paradigm to evaluate cognitive workload. The cognitive workload from twenty-five healthy participants was measured during a tilt-ball game while tones were presented in the background to generate event-related potentials (ERPs) in electroencephalographic (EEG) data. In the game, participants were instructed to move the ball to highlighted targets and avoid moving obstacles. The game's difficulty level was manipulated (easy, medium, hard) by adjusting the number and speed of the moving obstacles. The difficulty levels were presented in a random order during multiple short runs to minimize the effects of habituation, fatigue, and boredom. The behavioral results showed that greater task difficulty resulted in a significant decrease ($p < 0.001$) in game performance, i.e., participants achieved few targets with a high collision rate. To evaluate cognitive workload, we measured the amplitude of early ERP components (N1, P1, and P2) corresponding to the involuntary attention orienting response. The amplitude of the N1 component decreased significantly ($p = 0.029$) with an increase in cognitive workload.

These findings suggest that the early ERP component, specifically the N1, corresponds to attention orienting response, and that the task difficulty modulates it. This study provided evidence that the inverse relationship between ERP components and cognitive workload can be reliably assessed by controlling for other factors such as habituation or boredom during a single task paradigm.

4.3 Introduction

The efficient and effective allocation of attentional resources during demanding tasks is important to maintain performance (Kramer et al., 1983). Such demanding tasks increase cognitive workload with a corresponding reduction of available attentional resources for other tasks. If these resources are depleted below a certain threshold, cognitive processing for additional tasks can be delayed or impeded (Carryl, 2012). Therefore, we need an objective and accurate measure of cognitive workload to understand how attentional resources are allocated during the performance of a task. Such an accurate measure of cognitive workload may have numerous advantages, including the ability to assess how difficulty levels of a task affect cognitive workload. This measure can also be used as a gauge of how well learned a task such as piloting of aircraft, driving a car, or monitoring radar is. This measure may help to enhance user-task interaction according to one's cognitive state (Dyke et al., 2015a). Recently, electroencephalography (EEG) based event-related potential (ERP) methods have been used extensively as an objective measure of cognitive workload. ERP based methods that evaluate cognitive workload can be divided into two different paradigms based on the task that participants perform.

In dual-task paradigms, the cognitive difficulty is manipulated using two tasks performed at the same time. The main task is termed as the primary task, and the secondary is used to add or manipulate the difficulty of the primary task. For example, Ullsperger et al. (2001) used a dual-task paradigm to evaluate cognitive workload in which monitoring a gauge was the primary task; varying the difficulty of this task using a secondary arithmetic task. It is well established in dual-task literature that the amplitude of ERPs decreases with an increase in task difficulty (Baldwin et al., 2004; Blanco et al., 2006; Shaw et al., 2018; Solís-Marcos & Kircher, 2019; Ullsperger et al., 2001). However, these dual-task paradigms require significant attentional resources, which fatigue the participants quickly (Allison & Polich, 2008). Also, the introduction of a secondary task can induce additional cognitive workload; therefore, it becomes hard to measure the exact workload associated with the primary task (Miller et al., 2011). Single task paradigms were introduced to address the limitations of dual-task paradigms.

In single task paradigms, the participants perform a single task at predefined levels of workload (i.e., easy, medium, and hard). Separate auditory stimuli are presented to generate ERPs. These auditory stimuli can be related to the task, where task completion depends on the stimuli. For example, the color of the target to hit during a task (Causse et al., 2015). Alternatively, the auditory stimuli can be irrelevant to the task; for example, De Pascalis et al. (1987); Shucard et al. (1981); Shucard et al. (1977) used irrelevant tone pairs during a cognitive engagement task. In these studies, the amplitude of ERPs corresponding to these tone pairs decreased with an increase in cognitive workload. After these, several studies have employed single task paradigms with task-irrelevant auditory stimuli to evaluate cognitive workload and reported a decrease in amplitude of ERPs with an increase in cognitive workload (Allison & Polich, 2008; Causse et al., 2015; Combs & Polich, 2006; Deeny et al., 2014; Dyke et al., 2015a; Gaal et al., 2007; Miller et al., 2011; Takeda et al., 2016).

All these studies used same task presentation, where each predefined level was presented in ordered blocks of easy, medium, and hard. In such a presentation, it can be difficult to distinguish whether the change in the amplitude of ERP components is due to actual cognitive workload variation or due to the habituation or fatigue as the participants move from first to the last block. Therefore, in the present study, we modified the task presentation in anticipation of minimizing the effect of habituation, fatigue, and boredom. Instead of presenting a task in ordered blocks of easy, medium, and hard we divided the task presentation into multiple short runs. In each run, the three difficulty levels were presented in a random order for a very short duration.

In this study, this novel task presentation was used with infrequent task-irrelevant auditory stimuli. These irrelevant auditory stimuli can generate specific ERP components based on the novelty and the task associated with the stimuli (for discussion see (Ghani et al., 2020a)). ERP components also highlight neural resources and stages of stimulus/information processing (Sokhadze et al., 2017). Based on the stage of information processing, the ERP components can be divided into perceptual (e.g., N100), cognitive (e.g., P300), and response (e.g., lateralized readiness potential (LRP)) (Sokhadze et al., 2017). In this study, we only looked at early ERP components such as N1, P1 and P2 because unlike Allison and Polich (2008), no instructions were given to the participants regarding auditory tones. These background tones were considered to capture perceptual resources to generate early ERP components corresponding to involuntary early attention orienting response to the auditory stimuli (Näätänen & Michie, 1979). Based on the previous literature, we predicted that the amplitude of early ERP components would decrease with an increase in cognitive workload.

4.4 Method

4.4.1 Participants

A total of 25 healthy young adults (10 females; age range 20-30 years; mean age 26) were recruited via advertisements on university notice boards. Participants were advised not to take any form of caffeine before the experiment. Initial contact form was given to the participants on arrival at the laboratory which contained screening information (caffeine intake, neurological disorders, and hearing loss). After screening, participants gave informed written consent prior to any data collection. They received a $20 gift voucher for participating in the study. This study was approved by the Auckland University of Technology Ethics Committee (AUTEC).

4.4.2 Task

The task involved in this study is a custom tilt-ball game. In this game, participants moved a ball by tilting an iPad to place the ball in one of the four randomly highlighted targets, while avoiding moving obstacles. **Figure 4.1** shows this task.

The difficulty level of the task was manipulated by adjusting the speed and number of moving obstacles. The easy level had two moving obstacles, while the medium and the hard level had three and four moving obstacles, respectively. As shown in **Figure 4.1**, there is one vertical and one horizontal track for the moving obstacles. Both these tracks are eight units long, and the speed of the moving obstacles was defined based on this track length. For example, in the easy level, the speed of each moving obstacle was defined as one unit per second. Similarly, the medium and the hard level had a speed of three and five units per second, respectively.

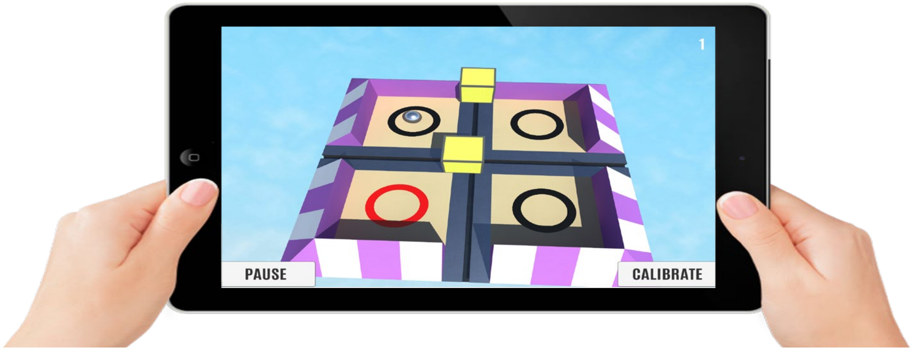

Figure 4.1 Shows a custom game with four targets (circles), a target highlighted in red, silver ball, and two moving yellow obstacles.

4.4.3 Procedure

After the participants gave their consent, they were seated on a comfortable chair and were encouraged to adjust the chair. After sitting, the participants were given an iPad and oriented to the task. The participants received one point each time they moved the ball to the highlighted target, and one point was deducted when they hit a moving obstacle. Two points were deducted if they fell out of the arena. After each block, the participants were asked to rate the difficulty of the task on a numerical rating scale (from 1 "Very easy" to 10 "very hard"). The total points a user attained in a block (targets), the speed of obstacle, the number of obstacle collisions (collisions), and subjective ratings (ratings) were used to quantify the absolute and relative difficulty of each level for each participant.

Participants were given a practice run of 2 min to familiarize themselves with the game. In the experimental session, there were eight runs of 6 min. In every run, three difficulty levels (easy, medium, and hard) were presented in a random order where each level lasts for two-minute blocks. This randomization was done using a MATLAB code, which gave us eight random combinations of three levels (easy, medium, and hard). Task presentation is shown in Fig. 2, with three levels of cognitive workload highlighted in different colors.

While the participant played the game, 1000 Hz tones (100ms duration, 10ms rise/fall time, 95 dB SPL) were presented over HP ELITEDESK computer speaker about 40 cm behind the subject's head. These tones were presented in the background and no instruction was given to the participant. The interstimulus interval varied randomly between 6 and 10 s. There were 45 tones presented during each run. As there was a total of eight runs per participant, as shown in **Figure 4.2**, a total of 360 tones were presented to a single participant while performing the task.

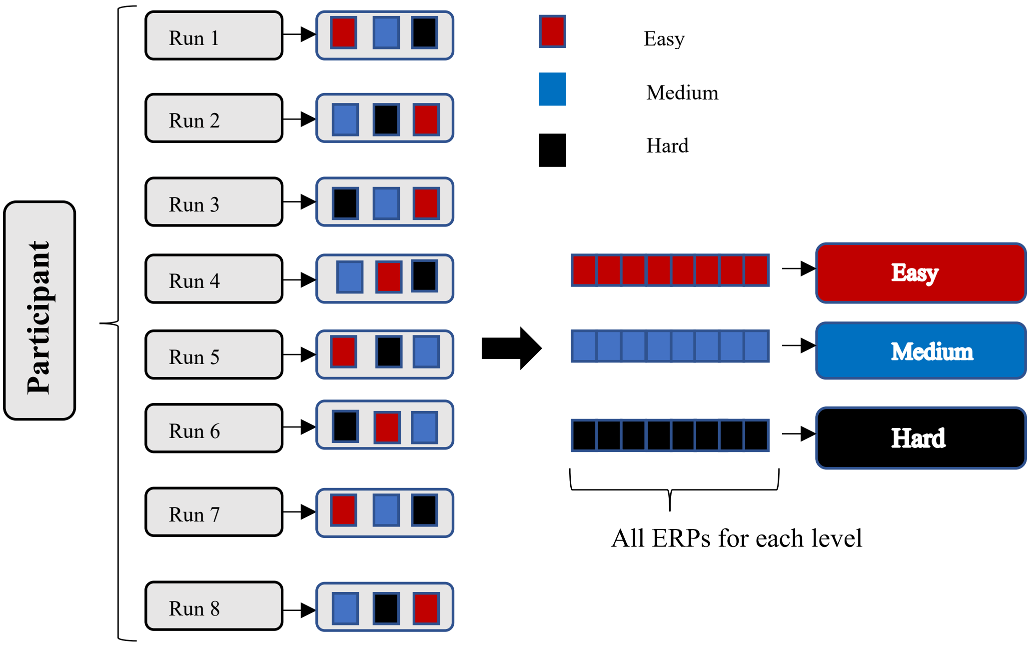

Figure 4.2 Shows the procedure of presenting the primary task where three levels of workload are presented in random order during eight separate runs.

4.4.4 Recordings

The electroencephalographic (EEG) signals were recorded with an EEG quick cap and 40-channel Nuamps EEG amplifier (Compumedics, Germany). Silver-Silver chloride electrodes were used. EEG data were recorded from 17 scalp sites (Fp1, Fp2, F3, Fz, F4, FC3, Fcz, F4, C3, Cz, C4, Cp3, Cpz, Cp4, P3, Pz, and P4 according to international 10–20 system) with A2 (right mastoid) as a reference. The impedance of all the electrodes was kept below 5kΩ. Raw EEG data were recorded using a 50 Hz notch filter with frequency ranging from DC to 100 Hz. After sampling, the EEG signals were imported into EEGLAB for further processing.

4.4.5 Data Analysis

Three measures of game difficulty were evaluated (e.g., targets, collisions, and ratings). The data were assessed by applying three separate repeated measures analysis of variance tests with level (easy, medium, and hard) and the measures of game difficulty (targets, collisions, and ratings) as main terms.

For event-related potential (ERP) data, following pre-processing steps were used. First, the data were filtered using a bandpass filter (0.05 Hz–30 Hz). After bandpass filtering, the ERPs were computed using a window of -200ms to 800ms relative to the onset of the individual stimulus (auditory tone). Epochs in which the signal exceeded 100µV on any channel were excluded from the analysis. In this study we recorded FP1 as an indicator of electro-ocular activity and the epochs highly effected by this activity were visually removed from the data. Following these two steps of data rejection/selection, on average, we got 332±11epochs across 25 participants which were used to calculate the grand average ERPs. The grand-average ERP waveform for each level (collapsed across all runs) was calculated. The mean amplitude for each component was then calculated using the approach suggested by Handy (2005) and used in Miller et al. (2011). It recommends centring a narrow time window around the peaks in the grand average ERP waveform. We averaged the ERP waveforms of three levels (easy, medium, and hard) to get a single ERP waveform. This ERP waveform was then used to mark narrow time windows across three prominent peaks.

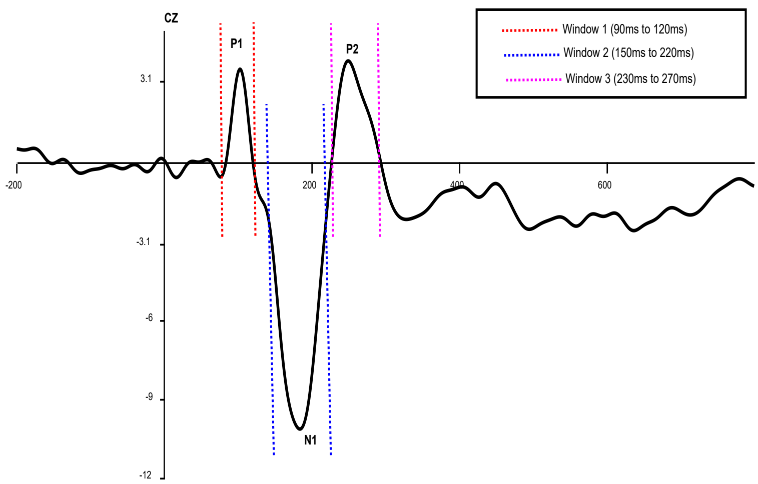

Figure 4.3 Shows the average waveform of easy level with highlighted time windows and outcome variables for CZ.

Accordingly, the time windows used were as follows: P1 = 90ms to 120ms; N1 = 150ms to 220ms; and P2 = 230ms to 270ms for three midline electrodes (Fz, Cz, and Pz). These defined components (P1, N1, and P2) have been used extensively in cognitive workload evaluation as they represent initial involuntary attention to the stimuli (Allison & Polich, 2008; Dyke et al., 2015a; Takeda et al., 2016). Therefore, the mean amplitudes of these components (P1, N1, and P2) from three midline electrodes (Fz, Cz, and Pz) were used as outcome variables in this study. **Figure 4.3** highlights these outcome variables. These outcome variables were separately subjected to repeated measures ANOVAs with levels (easy, medium, and hard) and outcome (mean amplitude) as the main terms. Finally, the Tukey post-hoc analysis was used to compare individual means. Additionally, Cohen's d effect sizes are also provided when appropriate.

4.5 Results

Performance parameters from the task (targets, collisions, and ratings) were used to quantify cognitive workload associated with each level. ERP data were then used to verify this quantification of cognitive workload. Other recorded data such as sex, gaming experience, and eyesight were not included in this analysis.

4.5.1 Performance parameters and subjective ratings

The performance data were assessed by applying three separate repeated measures analysis of variance tests with level (1: easy, 2: medium, and 3: hard) and the measures of game difficulty (Targets, Collisions, and ratings) as main terms. All the performance parameters, targets $F(2,573) = 287.3$, $p < 0.001$, collisions $F(2,573) = 205.2$, $p < 0.001$, and ratings $F(2,573) = 137.6$, $p < 0.001$ revealed a statistical difference between the three difficulty levels.

The post hoc analysis also revealed that level 3 was the hardest (lowest targets, highest collisions). All these results are highlighted in **Figure 4.4 (A, B, and C)**. After validating three distinct levels of workload based on performance measures (targets, collisions, and subjective ratings), the amplitude of ERPs was looked at for evaluation of cognitive workload.

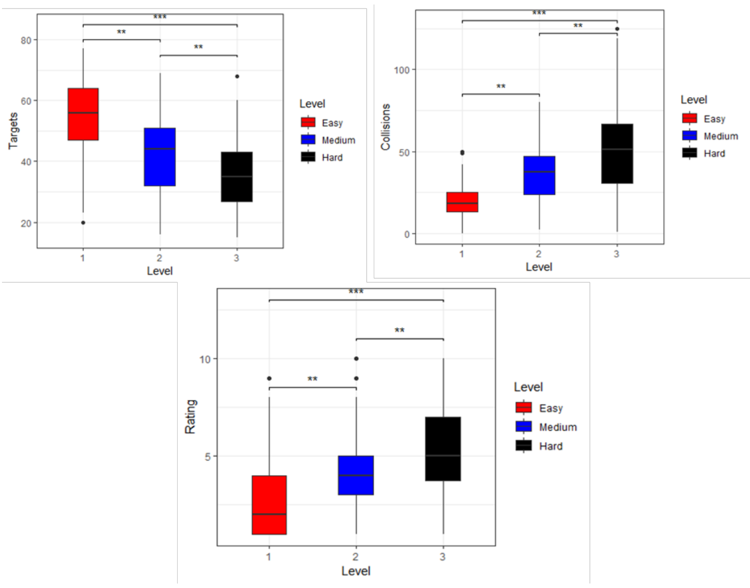

Figure 4.4. (A) shows targets achieved during each level: highest for level 1. (B) shows collisions with the obstacles during each level: lowest for level 1. (C) shows ratings given to each level: lowest for level 1.

4.5.2 ERP based measures

Figure 4.5A illustrates the grand average ERPs from midline electrodes (Fz, Cz, and Pz) for each level. The P1, P2, and N1 components are evident. It is evident from **Figure 4.5A** that the amplitude of the harder level is lower as compared to the easy level. Mean amplitudes of each component were subjected to separate 3 x 3 (Levels x Channel) repeated measures ANOVAs. There was no (Level x Channel) interaction for any component; therefore, the main effects for three midline electrodes were used for further analysis. The statistical analysis revealed a significant difference between levels only for the N1 component F (2,196) = 5.019, p = 0.029, η_ρ^2= 0.264. Additionally, there was no statistical difference between the levels for P1 and P2 component [F (2,196) = 2.2, p=0.1 and F (2,196) = 1.59, p=0.2]. **Figure 4.5B** highlights the amplitude distribution for three difficulty levels (easy, medium, and hard) across the scalp for the N1 component.

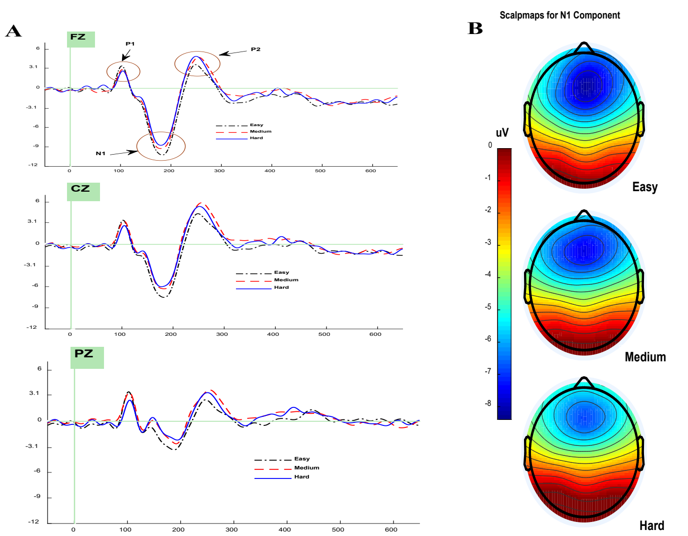

Figure 4.5: A) Grand-average ERPs of 25 participants recorded from FZ, CZ and PZ time-locked with auditory tones. Data from three levels (easy, medium, and hard) is superimposed. B) Scalp maps of easy, medium, and hard for the N1 component.

In post hoc analysis, pairwise means comparison was performed to compare the means of each level for the N1 ERP component. Post hoc analysis with respective means is shown in **Table 4.1**. Post hoc analysis revealed that for the N1 component, the mean amplitude of easy and medium levels was significantly larger than the hard level (Easy > Hard, p 0.0171: Medium > Hard, p 0.0230). Although the mean amplitude of the easy level for the N1 component was greater than the medium level, it was not significant (Easy > Medium, p = 0.9).

Table 4.1 Post hoc analysis of the N1 component.

ERP Components	Level	Mean	Level	Mean	p-value	Effect-size (d)
N1	Easy	-6.37	Medium	-6.51	0.8639	0.03
	Easy	-6.37	Hard	-5.62	0.0171*	0.18
	Medium	-6.51	Hard	-5.62	0.0230*	0.22

4.6 Discussion

The presented study examined the amplitude of early ERP components (N1, P1, and P2) elicited by a task-irrelevant auditory tone during a custom tilt ball game. This game had predefined levels of workload (easy, medium, and hard) which were presented in random order for short durations to minimize fatigue or boredom. Scores from the performance parameters (targets achieved, collisions, and subjective ratings) were at their lowest during the hard level of the game (i.e., fewer targets achieved with a high collision rate). The amplitude of the N1 component decreased significantly with an increase in cognitive work- load but changes in the amplitude of the P1 and the P2 components in relation to cognitive workload were not statistically significant.

As discussed in the introduction the irrelevant auditory tones were expected to consume perceptual resources corresponding to the involuntary early attention orienting response (Kramer et al., 1983; Wickens et al., 1984), resulting an effect only on early ERP components such as N1, P1, and P2. The present study confirmed these expectations using a novel presentation of a customised task alongside irrelevant auditory probes. The task was presented in a random order of easy, medium, and hard across multiple short durations. Unlike the study by Allison and Polich (2008) no instructions were given to the participants regarding the irrelevant auditory tones. The results of this study showed that the amplitude of early ERP components, specifically the N1 component, corresponded to the involuntary attention orienting response which was modulated by task difficulty. These results were in line with the previous study by Takeda et al. (2016) which investigated the N1 component specifically using task-irrelevant auditory probes. Importantly, the present study suggests the possibility that cognitive workload associated with a task can be evaluated using a single task paradigm by minimizing factors such as habituation, fatigue, and boredom.

If we look at each component separately, the P100 is more often implicated when we use a somatosensory stimulus (Desmedt et al., 1983), therefore it could be due to the nature of the stimulus (auditory) used in this study that it did not generate a robust P1 component. On the other hand, both N1 and P2 ERP’s can be generated robustly using an auditory stimulus (Deeny et al., 2014; Horat et al., 2016; Takeda et al., 2016). So, why was task difficulty reflected in the N1 component and not the P2 component? Although hypothetical, it is possible that the N1 and P2 components consume attentional resources at different processing stages: that is N1 reflects the consumption of early perceptual resources while P2 reflects the consumption of later processing resources (Sokhadze et al., 2017). In the present study no instruction was given to the participants regarding the task-irrelevant tones therefore these tones may have captured attention involuntarily. In a study by Näätänen and Michie (1979), the N1 was considered to be associated with stimulus filtering and involuntary attention whereas the P2 component was thought to be associated with auditory processing as reported by Rif et al. (1991).

This single task paradigm to evaluate cognitive workload has broad implications. It is easy to implement and provide an actual measure of cognitive workload during the task. Notably, this paradigm could be employed in various rehabilitation tasks such as force tracking and myoelectric prosthesis control (Deeny et al., 2014). This could then be used to develop brain-computer interfaces (BCIs) for different rehabilitation settings. Although, the task-irrelevant single task paradigm has numerous advantages, but it is prone to habituation of the task-irrelevant stimuli. This study provided a way of distributing the habituation effect across three levels, but further replications of this paradigm are needed to completely minimize or remove this habituation effect. Another limitation of this paradigm is the equipment used which is currently usable only in laboratory settings. The use of electrode caps and electrode gels for EEG recordings restricts the usability of this technique in rehabilitation settings. However, new EEG recording devices might allow the use of ERPs in real-life (Debener et al., 2012). The combined use of this proposed technique with new recording devices could facilitate interactions between the patients and clinicians in a rehabilitation setting.

4.7 Conclusion

The present study has demonstrated that the amplitude of the N1 ERP component corresponds to an involuntary attention orienting response which can be modulated by cognitive workload. The amplitude of the N1 component decreased significantly with an increase in cognitive workload during a single task ERP paradigm with task-irrelevant auditory tones. The other early ERP component, P2 was shown to be associated with auditory processing rather than an involuntary attention orienting response. There was no significant relation- ship between the amplitude of the P2 component and cognitive workload. The current study demonstrated that the inverse relationship between ERP components and cognitive workload can be reliably assessed by controlling and limiting factors such as habituation or boredom during performance of the single task paradigm. However, further replications of this novel task presentation are required to implement it to real-world scenario.

4.8 Acknowledgement

We would like to thank Brain Research New Zealand (BRNZ) for sponsoring this research and Exsurgo Rehabilitation Limited, Auckland, New Zealand for the game development.

End of the published work

4.9 Summary

This chapter validates the efficacy of single-task ERP-based methods to evaluate cognitive workload by minimizing the effects of habituation. One issue with the single task ERP-based method, highlighted in the **Chapter 3** was habituation. In this study, the task was designed to have three distinct levels of cognitive workload (easy, medium, hard). A custom-made game (visuo-motor task) was used to produce three distinct levels of difficulty in the task as it was not possible to find commercially available games that clearly distinguished three distinct levels. These levels were presented randomly for short durations in anticipation of distributing the effect of habituation of stimuli across different levels. The key findings of this experimental study were:

- Single-task event-related potential (ERP) paradigms can provide a reliable index of cognitive workload irrespective of the habituation effect.
- The N1 ERP component has neural generators in the auditory association area, making it a critical component of evaluating cognitive workload using auditory stimuli.
- In agreement with the published literature (Allison & Polich, 2008; Miller et al., 2011; Takeda et al., 2016), this study supported the premise that auditory stimuli generate robust ERPs which can be used to evaluate cognitive workload.

These findings fully address objectives 3A and 3B listed in **Chapter 1**, which were to validate the efficacy of single-task ERP methods to evaluate cognitive workload and highlight the correlates of EEG/ERP associated with the cognitive workload. The subsequent chapter will implement the same methodology in a rehabilitation-like task.

Chapter 5. Cognitive workload evaluation during an exergame

5.1 Prologue

This chapter presents an experimental study to validate the efficacy of the same methodology presented in **Chapter 4** to evaluate cognitive workload using a rehabilitation-like task. This chapter first highlights the importance of cognitive workload evaluation in rehabilitation with the pros and cons of currently used methods. It then presents the concept of exergames in rehabilitation with the help of literature. A rehabilitation-like task was then designed to address the following thesis objective:

- To conduct an experimental study to validate the possibility of implementing single-task ERP methods to evaluate cognitive workload in a rehabilitation-like task.

This experimental study has been published in a peer-reviewed journal, and it is presented here with no modifications in the content. Few minor formatting modifications are made to facilitate reading (Ghani et al., 2021) . The supporting documents associated with this chapter can be found in the **Appendices**. These documents are participant information sheet (Appendix F), advertisement poster for recruitment (Appendix G), ethics approval letter (Appendix H) and sample size calculation (Appendix I).

Start of published manuscript 3.

Efficacy of a single-task ERP measure to evaluate cognitive workload during a novel exergame.

Ghani, U., Signal, N., Niazi, I. K., & Taylor, D. (2021, 2021-September-08). Efficacy of a Single-Task ERP Measure to Evaluate Cognitive Workload During a Novel Exergame [Original Research]. *Frontiers in Human Neuroscience, 15*(519). https://doi.org/10.3389/fnhum.2021.742384

5.2 Abstract

This study aimed to validate the efficacy of single-task event-related potential (ERP) measures of cognitive workload to be implemented in exergame-based rehabilitation. Twenty-four healthy participants took part in a novel gamified balance task where task-irrelevant auditory tones were presented in the background to generate ERPs in the participants' electroencephalogram (EEG) as a measure of cognitive workload. For the balance task, a computer-based tilt-ball game was combined with a balance board. Participants played the game by shifting their weight to tilt the balance board, which moved a virtual ball to score goals. The game was manipulated by adjusting the size of the goalposts to set three predefined levels of game difficulty (easy, medium, and hard). The participant's experience of game difficulty was evaluated based on the number of goals scored and their subjective reporting of perceived difficulty. Participants experienced a significant difference in the three levels of task difficulty based on the number of goals scored and perceived difficulty ($p < 0.001$). Post hoc analysis revealed the lowest performance for the hardest level. The mean amplitude of the N1 ERP component was used to measure the cognitive workload associated with the three

difficulty levels. The N1 component's amplitude decreased significantly ($p < 0.001$), with an increase in the task difficulty. Moreover, the amplitude of the N1 component for the hard level was significantly smaller compared to medium ($p = 0.0003$) and easy ($p < 0.001$) levels. These results support the efficacy of the N1 ERP component to measure cognitive workload in dynamic and real-life scenarios such as exergames and other rehabilitation exercises.

5.3 Introduction

In rehabilitation, the level of cognitive workload for an individual patient is, in part, dependent on the task difficulty. Task difficulty is related to variables such as the number of repetitions of the task and the intensity of the task or how *hard* the person is working (Brody, 2012). These variables are important for clinicians to consider when setting rehabilitation programs and lead the clinician to determine how challenging each rehabilitation task is for the individual and the optimal number of repetitions and intensity required to achieve good rehabilitation outcomes for each patient. In other fields a number of subjective procedures have been developed for measuring cognitive workload. In particular, modified Cooper–Harper Scale (Wierwille & Casali, 1983), the Subjective Workload Assessment Technique (Reid & Nygren, 1988), and the NASA-TLX are widely used (Hart & Staveland, 1988; Hill et al., 1992; Rubio et al., 2004). However, these subjective measures are insensitive to cognitive workload changes that occur *during* the task or rehabilitation session (Deeny et al., 2014; Eggemeier, 1988). Currently, there is no objective measure sensitive enough to evaluate cognitive workload during the performance of a rehabilitation task. Therefore, this study proposed an electroencephalogram (EEG) based paradigm to measure cognitive workload during rehabilitation.

EEG has the potential to measure cognitive workload with a high temporal resolution while allowing freedom of movement during data collection, thus facilitating adaptability to clinical, operational, or real-world settings (Casson et al., 2008; Kruse, 2007; Lan et al., 2007; Seneviratne et al., 2013). Remarkably, although efforts to use measures of cognitive workload such as event-related potentials (ERPs) in EEG are increasingly abundant in the literature for several real-life tasks (Allison & Polich, 2008; Causse et al., 2015; Kramer et al., 1995; Miller et al., 2011; Suzuki et al., 2005; Takeda et al., 2016), ERP measures of cognitive workload have not been adapted and applied to the field of rehabilitation. Our previous study evaluated the cognitive workload in three predefined difficulty levels (easy, medium, and hard) during a custom-made visuomotor task (Ghani et al., 2020b). The task used was a tilt-ball game (played on an iPad with participants sitting on a chair). The study involved 25 healthy young adults (age range 20-30 years). There were three predefined difficulty levels, and the target was to move the ball (by tilting an iPad) into highlighted goals while avoiding the obstacles. Goals scored, collisions with moving obstacles, and subjective ratings were used as performance measures. The results showed a significant decrease in the N1 ERP component with increased task difficulty. Similarly, both behavioral measures showed significant effects of task difficulty. For example, goals scored were significantly decreased, and subjective ratings were significantly increased when the task difficulty was increased from easy to medium to hard.

The current study aimed to validate the same approach to evaluating cognitive workload during rehabilitation settings. We developed a custom-made exergame with three predefined difficulty levels. Exergames incorporate exercises into on-screen computer games or use in clinical rehabilitation settings (Fitzgerald et al., 2010; Gil-Gómez et al., 2011; Harvey & Ada, 2012; van den Berg et al., 2016). The main idea behind introducing exergames into rehabilitation is to motivate and enhance engagement in rehabilitation (van den Berg et al., 2016). The exergame used in this study had two parts 1) the cognitive (tilt-ball game) and 2) the physical (balance board) components. We kept the challenge in the balance component of the task constant and to a minimum to ensure that the participants were preferentially focused on the cognitive component (tilt-ball game). Similar to our previous study, the current study utilized task-irrelevant auditory stimuli to generate ERP components, and no instructions for these stimuli were given to the participants. Hence, these stimuli were expected to consume involuntary attention orienting response highlighted by the early ERP components (N1, P1, P2) (Ghani et al., 2020a; Ghani et al., 2020b; Näätänen & Michie, 1979).

Out of these early ERP components, the N1 ERP component is strongly associated with stimulus filtering and involuntary attention orienting (Ghani et al., 2020b; Näätänen & Michie, 1979; Takeda et al., 2016). The N1 ERP component is also considered to mark stimulus detection and perhaps later stages of sensory processing in conjunction with later ERP components (Fogarty et al., 2020). These properties make the N1 ERP component the most suitable to look at during a task-irrelevant auditory ERP paradigm. Therefore, we selected the N1 ERP component's amplitude concerning cognitive workload and hypothesized that the N1 ERP component's amplitude would decrease with the increased cognitive workload.

5.4 Materials and Methods

5.4.1 Participants

An a priori power analysis was conducted using G*Power3 (Faul et al., 2009) with previously reported effect size ($\eta_\rho^2 = 0.264$) (Ghani et al., 2020b), power (β = 0.8), and significance level (α = 0.05). A total of twenty-four healthy young adults (11 females, age range: 20-30, mean age: 25±3.4) were recruited via advertisements through university networks and word of mouth. People with a neurological disorder, hearing loss, recent head injury, or metal implants were excluded from the study. Participants were advised to avoid caffeine before the experiment and asked about their caffeine intake for the day on arrival. All the participants signed a written informed consent before the experiment and received a $20 gift voucher.

5.4.2 Task

The exergame rehabilitation task involved playing a tilt-ball game via a balance board. Participants stood on a balance board which could tilt in multiple directions up to an angle of ten degrees. While standing on the board, the participant could control the tilt direction and angle by moving their center of mass. The custom designed tilt-ball game (see **Figure 5.1A**) was installed on an android phone embedded in the center of a balance board, as shown in **Figure 5.1B**. The participant tilted the balance board, and consequently the phone, to control the ball within the tilt ball game. The tilt-ball game was projected from the phone to a screen in front of the participants. This complete setup is shown in **Figure 5.1C**.

The tilt-ball game had eight different goalposts, a soccer ball, and a moving obstacle. One of the eight goalposts was highlighted randomly, and the task was to move the soccer ball into the highlighted goalpost by tilting the balance board. The participant scored one point for each goal. The absolute difficulty of the task was manipulated by adjusting the size of the goalposts. Three absolute difficulty levels (easy, medium, and hard) were predefined. The easy level had a large goalpost (1 unit long) as compared to medium (0.8 unit long) and hard (0.6 unit long) levels.

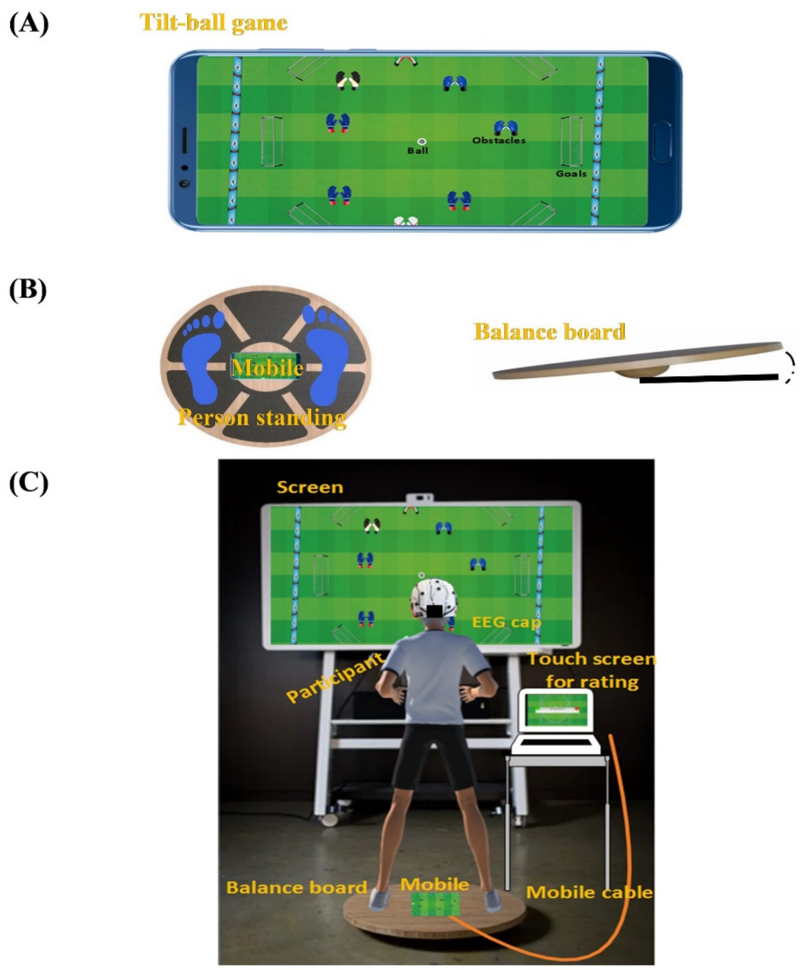

Figure 5.1 (A) shows a tilt-ball game on an android device. **(B)** shows a balance board with a tilt angle and top view of a person standing on the balance board. **(C)** shows the complete study setup.

5.4.3 Procedure

After participants had provided written informed consent, they undertook six minutes of practice to familiarize themselves with the exergame. They were then prepared for EEG recording (Section " **EEG Data Collection and Processing**"). Data collection was undertaken in six separate runs of nine minutes each. In each run, three predefined difficulty levels (easy, medium, and hard) were presented in a random order (randomization was done using a MATLAB code), where each level lasted for two minutes. After each two-minute block, a one-minute break was given. In this break time, the participants were instructed to sit on a chair and asked to subjectively rate the task difficulty of the block on a numeric scale (1= "Very easy" to 10 = "very hard"). This presentation is shown in **Figure 5.2**, with three difficulty levels highlighted in different colors. The participants experience of task difficulty was evaluated in two ways; 1) the number of goals scored during each level and 2) the subjective rating of perceived task difficulty.

During the task, 1000 Hz tones (100ms duration, 10ms rise/fall time, 95 dB SPL) were presented over a pair of speakers placed about 50cm behind the participant. These tones were presented in the background, and no instruction was given to the participant about the auditory stimuli. According to the literature, the interstimulus interval can affect the amplitude of ERP components (Gonsalvez et al., 2007). Therefore, based on the study of Allison and Polich (2008), the auditory tone interstimulus interval was varied randomly between 6 to 10s. There were 45 tones presented during each run, with 270 tones presented to a single participant while performing the task.

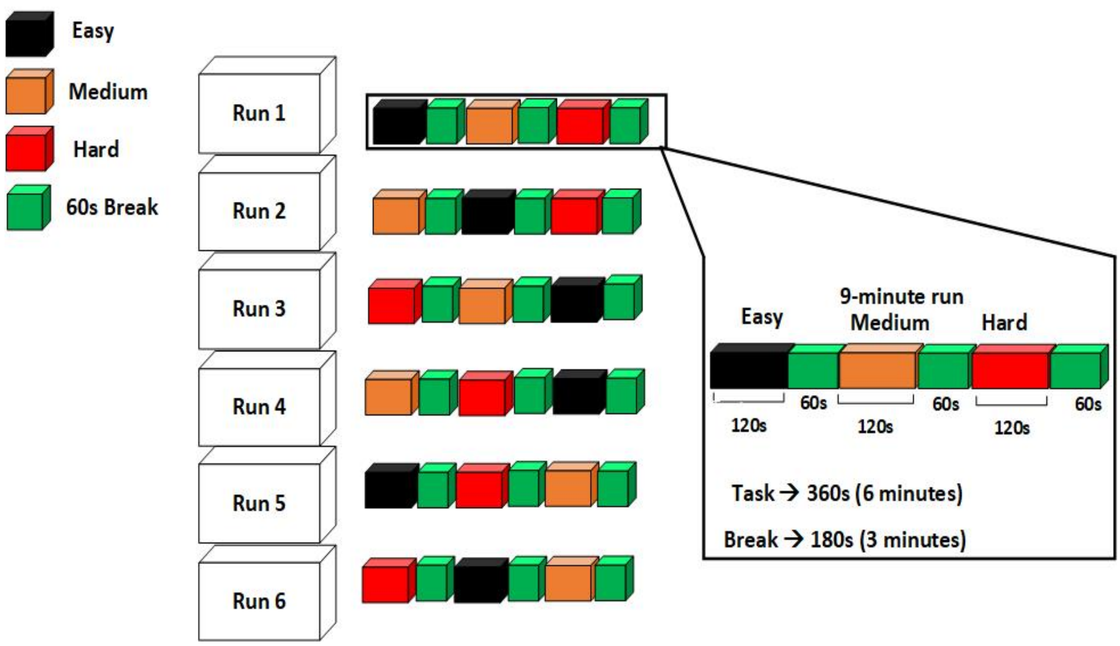

Figure 5.2 shows the procedure of presenting three difficulty levels in random order during six separate runs.

5.4.4 EEG Data Collection and Processing

The EEG data was recorded using a 64 channel Brainwave EEG cap with a REFA amplifier (TMSi, Twente, The Netherlands) at a sampling rate of 2048Hz. EEG data was recorded from all 64 scalp sites according to a 10-20 electrode system (Homan, 1988). The ground electrode was placed at AFz, and both mastoids (M1 and M2) were used as a reference for the recording. The impedance of all the electrodes was kept below 10kΩ. The online filter settings were DC -100 Hz, where a 50Hz notch filter was also used during the recording of raw data. The raw EEG data were pre-processed offline using EEGLAB (version 14.1.1) (Delorme & Makeig, 2004) and ERPLAB (version 6.1.4) (Lopez-Calderon & Luck, 2014) running on MATLAB 2015b (The MathWorks, Inc, Natick, MA, USA.).

The PREP pipeline (version 0.55.1) (Bigdely-Shamlo et al., 2015) was used to remove and interpolate bad channels, remove line noise, and find the average reference. Then the data was high pass filtered at 1Hz before independent component analysis (ICA). ICA and IClabel (Pion-Tonachini et al., 2019) were used to visually remove noisy components such as eyeblinks or other muscle artifacts. The data was then bandpass filtered at (0.05Hz – 30Hz). Following pre-processing, epochs were extracted from -200 to 1000ms to the stimulus and were baseline corrected using the pre-stimulus period. The epochs obtained were then subjected to the ERPLAB artifact detection algorithm of moving window threshold (Lopez-Calderon & Luck, 2014). A 200ms window width and a 100ms step were defined with a threshold of ±100µV. The epochs in which the signal exceeded ±100µV on any channel were rejected.

The grand-average ERP waveform for each predefined difficulty level (collapsed across all runs) was calculated. The latency window of the N1 ERP component for all three predefined difficulty levels (easy, medium, and hard) was defined as previously reported (Ghani et al., 2020b). The reported method suggests placing a narrow time window around the peaks in the grand average ERP waveform of the Cz electrode. The grand averaged ERP waveform was obtained by averaging the waveform of three levels (easy, medium, and hard). This ERP waveform was then used to mark narrow time windows across three prominent peaks. The latency window for the N1 component obtained from this method was 150ms to 230ms for three midline electrodes (Fz, Cz, and Pz). This latency information was provided to ERP measurement tool (Lopez-Calderon & Luck, 2014) to extract amplitude of the N1 component. After all the pre-processing steps on average 10 ± 5 epochs were rejected per level for each participant. However, the number of epochs across each level (easy, medium, and hard) were kept constant.

5.4.5 Statistical Analysis

The statistical analysis was divided into two phases 1) analysis of performance data and 2) analysis of physiological data. Two separate repeated measures analysis of variance (ANOVA) tests with main terms of predefined difficulty level (easy, medium, and hard) and the measures of experienced difficulty (goals scored and subjective rating of difficulty) were used for the analysis of performance data. The goals scored and ratings of difficulty for each level were averaged across six runs for each participant. For the physiological data, a 3x3 (level x channels) repeated measures ANOVA with main terms of predefined difficulty level (easy, medium, and hard) and the measure of cognitive workload (mean amplitude of N1) was used. The data was then rearranged by averaging across three electrodes for each level. Finally, the data was subjected to a post-hoc pairwise comparison of each level (easy, medium, hard). The Bonferroni adjusted values are reported for all post-hoc comparisons. Conventional degrees of freedom are reported throughout the results. Additionally, effect sizes were reported when required. For post-hoc correlation analysis, we looked at the correlations between the change in outcome measures (Easy – Hard) using Pearson's correlation. The outcome measures used in this analysis were behavioral measures (goals scored, subjective ratings) and physiological measures (the N1 ERP component). The amplitude of the N1 ERP component was the average taken from three midline electrodes (Fz, Cz, and Pz). The correlation between the change in the amplitude of the N1 ERP component and change in goals scored, the change in the amplitude of the N1 ERP component and change in subjective ratings, and the change in subjective ratings and change in goals scored, was examined separately.

5.5 Results

Task performance parameters (goals scored and difficulty ratings) were used to measure perceived difficulty to ensure that the participants had experienced three predefined levels of task difficulty (easy, medium, and hard). The N1 ERP component was then used to measure cognitive workload associated with the three predefined levels of task difficulty. Finally, to look at the effect of increasing task difficulty on attentional demands a correlation analysis between behavioral and physiological measures was conducted.

5.5.1 Behavioral Results

Both measures of perceived difficulty goals scored $F\ (2,46) = 26.9$, $p<.001$, $\eta_\rho^2 = .438$ and difficulty ratings $F\ (2,46) = 32.2$, $p<.001$, $\eta_\rho^2 = .483$ showed that the participants experienced significant differences in the three levels of task difficulty. Post-hoc analysis revealed that the number of goals scored during the easy level was significantly greater than goals scored during the medium ($t(69) = -3.29$, $p<.005$) and hard ($t(69) =$

7.32, p<.001) levels, respectively. Similarly, the goals scored during medium level were significantly greater than goals scored during hard level (t(69) = 4.03, p<.001). For the second measure of perceived difficulty, the subjective ratings given by the participants to the easy level were significantly lower than medium (t(69) = -3.64, p = .001) and hard (t(69) = -8.01, p<.001) levels. Similarly, the medium level received a lower rating than the hard level (t(69) = -4.37, p<.001). These results are shown in **Figure 5.3A** and **B**.

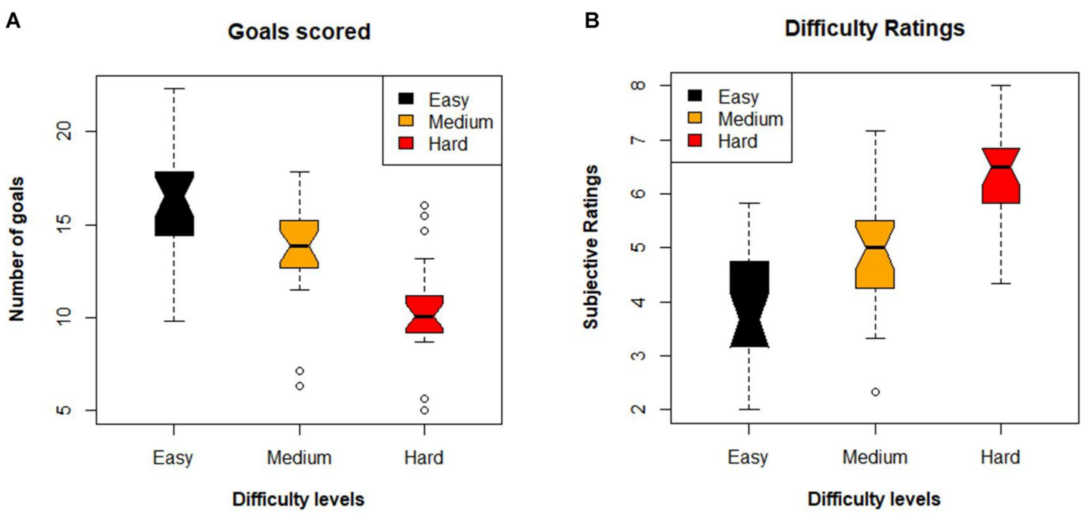

Figure 5.3 (A) shows the boxplots of the mean goal scored during each difficulty level. **(B)** shows the boxplots of the subjective difficulty ratings. The has outliers so whiskers represent one and a half times the interquartile range (1.5 × IQR).

5.5.2 Electrophysiological Measures

Figure 5.4A illustrates the grand average ERPs for each predefined difficulty level (easy, medium, and hard). The P1, P2, and N1 components are evident, and the N1 ERP component is highlighted using a dotted circle. In the previous study, the N1 component's amplitude showed a significant cognitive workload change (Ghani et al., 2020b). Therefore, in this study, the N1 ERP component's amplitude from three midline channels (Fz, Cz., Pz) was evaluated as a measure of cognitive workload. There was no level channel interaction F (4,92) = 0.209, p = 0.933, η_ρ^2 = .005, and the statistical analysis revealed a main effect for predefined difficulty levels (easy, medium, and hard) for the mean amplitude of the N1 component F (2,46) = 94.6, p <0.001, η_{ρ}^{2} = .471. The effect of channel was also not significant F (2,46) = 1.026, p = 0.280, η_{ρ}^{2} = .012. The N1 ERP component exhibits a frontocentral scalp distribution (Parasuraman & Beatty, 1980), shown in **Figure 5.4B** for all three levels of predefined difficulty (easy, medium, and hard).

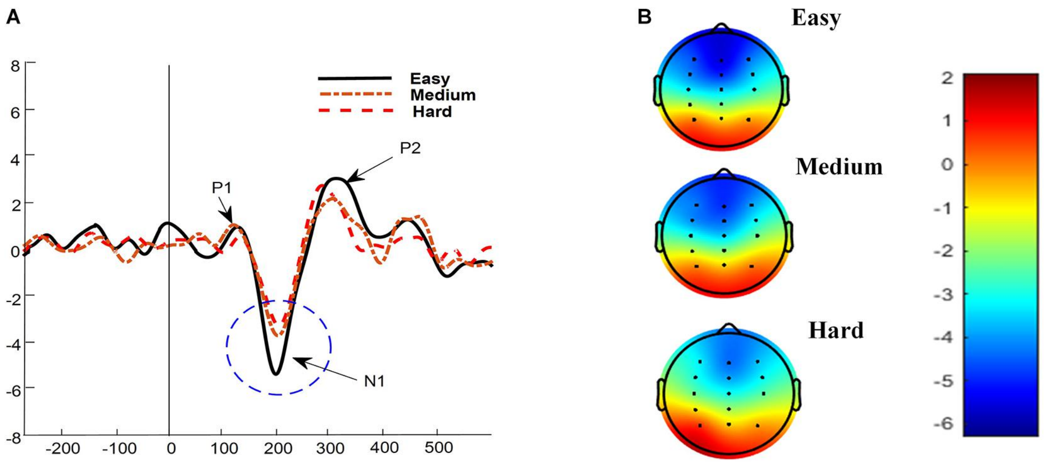

Figure 5.4 (A) shows a grand average ERP waveform of 24 participants: P1, P2, and N1 are evident. **(B)** shows scalp maps of the N1 component for three levels of cognitive workload.

Post hoc analysis with respective means, confidence intervals, and Cohen's d effect size is shown in **Table 5.1**. Post hoc analysis revealed that for the N1 component, the mean amplitude during the hard level was significantly lower than during the easy (Hard < Easy, t(69) = -3.84, p<.001) and medium levels (Hard < medium, t(69) = -2.28, p = .001). Similarly, the medium level's mean amplitude was significantly lower than the easy level (Medium < Easy, t(69) = -6.12, p<.001).

5.5.3 Correlation between electrophysiological measures and performance measures

The change in the physiological measure (the N1 ERP component) correlated significantly with the change in the number of goals scored (r(22) = 0.407, p = .049) as the difficulty increased from easy to hard. This suggests that as the performance difference increased, the difference between the amplitude of the N1 component between two difficulty levels also increased. On the other hand, the correlation between the change in the N1 ERP component and the change in subjective rating was not significant ($r(22) = 0.224$, $p = .293$). Change in both behavioral measures such as goals scored and subjective ratings were correlated ($r(22) = 0.642$, $p<.001$), highlighting the consistency between the performance difference and subjective ratings difference.

Table 5.1 shows the mean values and effect sizes from the post-hoc comparison.

ERP Component	**Level**	**Mean**	**95% Confidence Interval**		**Pairwise Comparison**	**p-value**	**Effect-size Cohen's d**
			Lower	Upper			
N1	Easy	- 3.64	-3.88	-3.40	Easy-Medium	<0.001	1.206
	Medium	- 2.73	-2.97	-2.49	Easy-Hard	<0.001	1.391
	Hard	- 2.31	-2.55	-2.07	Medium-Hard	0.0003	0.531

5.6 Discussion

The present study was designed to assess a single-task ERP method of evaluating cognitive workload to determine the possibility of using this method during rehabilitation. We intended to evaluate the cognitive workload associated with a novel exergame. Behavioural measures of task difficulty were recorded along with the EEG data. Behavioural results show that the performance of the participants decreased with an increase in task difficulty. On the physiological level, the amplitude of the N1 ERP component decreased significantly with an increase in task difficulty. These results were similar to those we obtained in our previous study (Ghani et al., 2020b) and were also in line with previous literature (Combs & Polich, 2006; Deeny et al., 2014; Kramer et al., 1995; Muller-Gass et al., 2007; Muller-Gass & Schroger, 2007; Suzuki et al., 2005). These findings validated our single task ERP paradigms' efficacy to evaluate cognitive workload during rehabilitation settings.

According to the literature, the most basic tasks in psychological research are composed of different component operations (Posner & Raichle, 1994). Some of these component operations are more cognitive in nature, and others are more motoric (e.g., the tilt-ball game in this study compared to standing on a balance board). In the cognitive load theory, there are three types of cognitive workloads 1) intrinsic (task difficulty), 2) extraneous (depends on external parameters), and 3) germane (depends on working memory). Therefore, the task difficulty alone cannot define cognitive workload (Sweller, 1988). We have argued that an increase in the difficulty of the cognitive component of our task (requiring participants to score goals in smaller goalposts) imposed a combination of three cognitive workloads and induced participants to allocate more attention to the tilt-ball game. This shift of attention varied with the cognitive task difficulty; for example, more attention was given to the tilt-ball game as the cognitive component of the difficulty varied from easy to medium to hard. In this study, the proposed relationship of the change in cognitive task difficulty and attention was validated by the correlation between the change in the N1 ERP component and the change in number of goals scored as the task difficulty increased from easy to hard. For example, as the task difficulty increased, the difference in goals scored increased, more attention was likely given to the task in compensation, affecting the amplitude of the task-irrelevant auditory evoked N1 ERP component.

In this study, the N1 ERP component was selected as a measure of cognitive workload based on two possible reasons 1) the neural generators of the N1 ERP component and 2) properties of the N1 ERP component. The N1 generators are located mainly in the superior temporal plane, including the primary and secondary auditory cortices and auditory association areas (Lü et al., 1992; Näätänen & Michie, 1979; Pantev et al., 1995; Woods, 1995). The auditory association area is known to mediate auditory and visual workload (for review, see Calvert (2001)). The finding that the auditory evoked N1 ERP component was significantly modulated by the cognitive workload imposed by the tilt-ball game suggests that the auditory association area is linked with a cross-modal capacity limit. Another supportive explanation is based on the generic properties of the N1 ERP component. As suggested by Dien et al. (1997); Grau et al. (2007); Picton et al. (1999), the N1 may also have sources in the frontal lobe, supporting links between the N1 and attention (Giard et al., 1994; Näätänen & Michie, 1979). Therefore, this association of the N1 ERP with both the cross-modal capacity limit and attention makes it a critical component in measuring cognitive workload using task-irrelevant auditory probes.

To date, there are no objective measures of the cognitive workload associated with any rehabilitation task, with health care practitioners relying on patient self-report. This study represents the first attempt to objectively quantify cognitive workload in rehabilitation settings, and the results are promising to investigate such methods. The N1 ERP component exhibited significant cognitive workload effects illustrating the inverse relationship between ERP (generated by task-irrelevant stimuli) amplitude and task difficulty. This paradigm is easily adaptable to research on various rehabilitation tasks where the cognitive workload is relevant. Wireless EEG caps used with this paradigm can enable real-time and offline EEG analysis for ecologically valid movements during various rehabilitation tasks. An additional advantage of the approach presented here is the sensitivity of the information acquired through a small number of electrodes. Although 64 channels of EEG data were obtained in this study, the results could have been obtained using only three midline electrodes (Fz, Cz, Pz) with a ground and a reference (Ghani et al., 2020b).

The current study was limited to healthy participants and was conducted using an exergame. Future efforts will extend to patient populations and be adapted to other rehabilitation tasks. The use of a traditional averaged ERP paradigm limits the implementation of this research into rehabilitation settings, but it provides essential insights into how cognitive workload affects ERPs in rehabilitation-like settings. These insights can then be used with more advanced techniques such as single-trial detection of ERPs (Jung et al., 2001) to implement this research in actual rehabilitation settings. Another advantage of this research in its current form is that it can be used to validate the clinical efficacy of available rating scales used in rehabilitation. The use of attentional reserve-based paradigm (ERPs) of assessing cognitive workload also has broad adaptability for comparing different tasks and strategies in various rehabilitation settings. Furthermore, combining the current paradigm with more sophisticated approaches such as source localization (Jatoi et al., 2014) and obtaining data from more channels (Michel & Brunet, 2019) can simultaneously address task difficulty, regional activation, and functional communication between different cortical regions (Rietschel et al., 2012) to examine the sensory, motor, and cognitive demands.

5.7 Conclusion

This study aimed to examine the efficacy of using ERPs as an outcome measure for cognitive workload in rehabilitation settings, specifically during exergames. The amplitude of the task-irrelevant stimuli generated N1 ERP component decreased significantly with an increase in task difficulty. This decrease in the amplitude of the N1 ERP component can be used to evaluate the cognitive workload of a rehabilitation task objectively. The current study examined only an exergame-based task in healthy participants, which requires replication in patients and adaptation to other rehabilitation settings. However, this single-task ERP approach with task-irrelevant stimuli is adaptable to various rehabilitation tasks as an objective outcome measure of cognitive workload.

5.8 Data Availability Statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

5.9 Ethics Statement

The studies involving human participants were reviewed and approved by Auckland University of Technology Ethics Committee (AUTEC). The patients/participants provided their written informed consent to participate in this study.

5.10 Author Contributions

UG designed and performed the experiments with consultation from NS, DT, and IN. UG derived the models and analyzed the data. IN assisted with data pre-processing and cleaning. UG wrote the manuscript in consultation with NS and DT. All authors contributed to the article and approved the submitted version.

5.11 Funding

This research was funded by Brain Research New Zealand (BRNZ).

5.12 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

5.13 Publisher's Note

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5.14 Acknowledgments

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End of the published work

5.15 Summary

A second experimental study was presented in this chapter, which looked at the same methodology presented in **Chapter 4** but with a rehabilitation-like task. The task used in this study was an exergame that had a balance-board and an on-screen computer game. Similar to the previous chapter, task-irrelevant auditory tones were presented to capture involuntary attention orienting responses. The findings of this chapter validated the previous finding of an inverse relationship between cognitive workload and attention orienting response. The key findings of this chapter were

- Single-task ERP-based method can evaluate the cognitive workload of a rehabilitation-like task.
- The N1 ERP component corresponds to an involuntary attention orienting response, and the cognitive workload of a rehabilitation-like task modulates it.
- There is a significant correlation between cognitive workload, task difficulty, and performance of a rehabilitation-like task.

These findings fully addressed objective 4 listed in **Chapter 1**, which was to validate the possibility of implementing a single-task ERP-based cognitive workload evaluation method in rehabilitation-like tasks. As the task in this study was designed in collaboration with clinicians and physiotherapists, the positive results of this study validated the robustness of ERP-based method to evaluate cognitive workload objectively during actual rehabilitation tasks. Furthermore, this study, the first experimental study, and the narrative synthesis contributed to the development of a clinical tool to assess cognitive workload during rehabilitation.

Chapter 6. Integrated Discussion and Conclusion

6.1 Prologue

This research was set out to establish a framework for objectively evaluating cognitive workload and to assess the methodological aspects of such evaluation methods. To fulfil this, an overview of the cognitive workload literature, a narrative synthesis of the ERP-based methods of evaluating cognitive workload, and two experimental studies investigating the robustness of EEG/ERP methods were included in the thesis. This chapter considers the need for an objective method of measuring cognitive workload in rehabilitation settings and provides an overview of the main findings of this research. Finally, this chapter discusses the implications of these findings for clinical practice and future research, as well as outlining the strengths and weaknesses of this research.

6.2 Task and difficulty selection in current rehabilitation settings

The process of rehabilitation after a neurological insult can assist patients in achieving functional independence (Ferrucci et al., 2007), preventing impairments (Patrick, 1997), and improving their quality of life (Brody, 2012). During rehabilitation, a patient may be assigned a particular task as a rehabilitation exercise. This task needs to be targeted to the patients individual needs, since many tasks may be difficult for some people but trivial for others (Burke et al., 2009). According to the literature, the rehabilitation task selected by the clinician should be meaningful to assist in neural plasticity in targeted brain regions to maximize motor learning for recovery (Levin et al., 2015; Winstein & Kay, 2015). Along with determining what the rehabilitation task is, the clinicians also considers other important factors that impact recovery, including determining the task difficulty, the number of task repetitions, and the extent of the cognitive workload induced by the task (Carr & Shepherd, 1989; Levin & Demers, 2021; Xing & Bai, 2020). When the task difficulty is too high or too low, it can overload or underload the brain, which can slow down recovery (Brownsett et al., 2014; Czyż, 2021). Setting an optimal level of task difficulty for the individual (Akizuki & Ohashi, 2015) enables a challenging cognitive workload that is conducive to recovery (Burke et al., 2009).

These concepts around task difficulty can be considered under the Challenge Point Framework (CPF) proposed by Guadagnoli and Lee (2004). Presenting a task at the optimal challenge point for each individual may maximize motor learning and expedite the rehabilitation process (Levin et al., 2015). The CPF is supported by evidence in various studies that have verified and confirmed that maximum motor learning occurs at the optimal challenge point (Akizuki & Ohashi, 2015; Hu et al., 2016; Onla-or & Winstein, 2008). Therefore, keeping track of a patient's optimal challenge point can assist clinicians in assigning and modifying task difficulty to achieve the optimal level for each patient, thus maximizing recovery. However, finding the optimal challenge points in rehabilitation can is difficult as it varies from patient to patient (Levin & Demers, 2021) and changes over time due to learning (Orrell et al., 2006), functional improvement (Lin & Dionne, 2018), fatigue or loss of interest (Burke et al., 2009).

Currently, clinicians do not have a clear method for finding the optimal challenge point, so they assign rehabilitation tasks based on observation and evaluate the patient's performance after several repetitions of the same task to determine whether they are progressing or not (Ferreira et al., 2014). Based on these observed performance parameters, clinicians determine if there is a need to change the task difficulty to meet the learning curve. So, the current method for finding challenge points is based solely on the clinician's observation, which is prone to human error. This approach is also limited due to its low sensitivity as clinicians are only able to look at performance metrics such as the task completion rate, response times, and accuracy. These metrics do not necessarily indicate cognitive workload during the task (Carryl, 2012).

There are subjective tools that are available to support decision making around cognitive workload, such as the NASA task load index (Hart & Staveland, 1988), the subjective workload assessment technique (SWAT) (Reid & Nygren, 1988), or the Modified Cooper-Harper scale (MCH) (Donmez et al., 2010) available. These tools have been verified and validated in several tasks such as driving (Takeda et al., 2016), piloting a plane (Causse et al., 2015), and during video game play (Allison & Polich, 2008; Deeny et al., 2014). Although these tools are helpful, their use in clinical practice raises potential issues, including, 1) It is possible that evidence-based recommendations (provided by subjective tools and the literature) differ from actual clinical practice, 2) these tools can be extremely long to complete and require considerable time for a clinician to assess, and 3) as these tools can be administered only after the task has been completed, they may not provide required information about the cognitive workload changes *during* the task. This highlights the need for an objective method of cognitive workload evaluation that can tap directly into a patient's brain and provide information about cognitive workload. Such information would aid clinical observations to speed up recovery during rehabilitation. Therefore, this research aimed to set up a framework for an objective cognitive workload evaluation method that can be used in rehabilitation.

To fulfil this aim, preliminary research was conducted to compare existing methods of objective cognitive workload evaluation to highlight the most suitable method for rehabilitation. We compared different cognitive workload evaluation methods based on the selection criteria constructed from parameters such as intrusion, sensitivity, diagnostic power, applicability, reliability, mobility, and time resolution. According to this comparison provided in **Chapter 2**, electroencephalogram (EEG) based event-related potential (ERP) methods were highlighted as the best-suited approach for objectively evaluating cognitive workload during rehabilitation. Therefore, my first primary contribution was to explore the ERP-based cognitive workload evaluation methods, which formed the basis for the two experimental studies completed as part of this thesis **Chapter 4**,**Chapter 5**

6.3 Overview of the findings

In my first primary contribution (**Chapter 3**, Manuscript 1), I explored ERP-based cognitive workload evaluation methods in the form of a comprehensive review. The goal of this review was to appraise ERP-based cognitive workload evaluation methods critically. Two types of ERP-based cognitive workload evaluation methods, dual-task and single-task were compared for their applicability in rehabilitation. As mentioned above, in rehabilitation, the task is carefully considered for each patient, and adding other tasks, such as is done in dual-task ERP-based methods, can add complexity and challenge to a task in an appropriate manner but could also cause the patient to become fatigued or overloaded (Allison & Polich, 2008; Miller et al., 2011). Due to these limitations, dual-task ERP methods were described as incompatible with rehabilitation in this review since rehabilitation did not always utilize dual-task performance. In contrast, the single-task variants of ERP methods were described as better suited to rehabilitation because often one task is assigned with no dual-task requirement. Furthermore, these single-task ERP-based paradigms with task irrelevant auditory stimuli were able to provide cognitive workload of the targeted task even during a potential dual task environment (Ghani et al., 2021; Xu et al., 2020).

The review synthesized information about individual ERP components and their relationship with different sources of cognitive workload (types of resources occupied). This highlighted the high diagnostic power of ERP-based methods as each ERP component (N1, P2, or P3) represented different sources of cognitive workload (Sokhadze et al., 2017). The P3 or later ERP components, for instance, provide information about the cognitive workload imposed by the cognitive aspect of the task, whereas N1 or earlier ERP components provide information about the perceptual aspects of the task. Moreover, the manuscript demonstrated that N1 and P2 of the early ERP components are also dependent on working memory resources, making them useful for assessing cognitive workload.

This information (knowing which ERP component to look at) can help save a lot of time when implementing the ERP-based method to evaluate cognitive workload and help researchers and clinicians focus on specific ERP components based on the type of task being performed. A motor task with task-irrelevant stimuli, for example, will show early ERP components, whereas a task in which participants pay attention to the stimuli (stimulus discrimination or counting stimuli), will generate later endogenous ERP components. It can also help clinicians adjust certain aspects of the task to target specific resources to challenge patients and maximize learning.

Single-task ERP methods have been used to evaluate cognitive workload, but there was minimal research evidence on which parameters can affect the evaluation criteria of these methods. In this review, several parameters of single-task ERP-based cognitive workload evaluation methods were highlighted, which can impact how these methods assess cognitive workload. According to the review's main findings, the evaluation criteria of cognitive workload using single-task ERP-based methods varied based on the type of task and stimuli used (Ghani et al., 2020a). Clinicians assign tasks according to each individual's needs; these can be cognitive or motor tasks. Hence, the flexible evaluation criteria of single task ERP methods (presented in this review) can allow clinicians to accurately identify either type of task's cognitive workload and can also evaluate both single and dual task performance. Furthermore, the information about the evaluation criteria can help researchers observe ERPs amplitude change in context to the task and stimuli. For example, the P3a component's amplitude variation with respect to cognitive workload changes for different types of tasks used in the literature. Combs and Polich (2006) used a tone discrimination task and reported an increase in the P3a component with an increase in cognitive workload. Whereas in a study by (Dyke et al., 2015b), a motor task with auditory stimuli was used, the authors reported a decrease in the amplitude of P3a with an increase in cognitive workload.

Finally, the review highlighted the limitations of single task ERP-based methods, among which habituation to the task and stimuli was highlighted. Single-task ERP-based methods for evaluating cognitive workload rely on a response to repeated stimuli (Luck, 2005), which can be affected by habituation (Mancini et al., 2018). However, the literature and studies included in the review implemented single-task ERP-based methods without considering the effect of habituation (Allison & Polich, 2008; Causse et al., 2015; Combs & Polich, 2006; Deeny et al., 2014; Dyke et al., 2015a; Horat et al., 2016). In these studies, each predefined difficulty level was presented in ordered blocks of easy, medium, and hard. In such a presentation, it would be difficult to distinguish whether the changes in the ERP components were due to actual cognitive workload change or habituation or fatigue as the participants progressed from one level to the next. Therefore, the efficacy of single-task ERP-based cognitive workload evaluation methods was questioned in my first experimental study, where I argued that as participants moved from one level of difficulty to another, the amplitude of the ERPs could be affected due to habituation rather than cognitive workload.

In the literature, a few studies have tried to limit the effect of habituation by using novel auditory stimuli compared to simple auditory tones (Causse et al., 2015; Combs & Polich, 2006; Frank et al., 2012; Goodin et al., 1983). Although the use of novel sounds minimized the effects of habituation, they interfered with the task (were intrusive) and could have distracted the participants (Ghani et al., 2020a). In my second primary contribution (**Chapter 4**,Manuscript 2), I addressed the issue of habituation to task-irrelevant simple auditory tones. In this experimental study, the task presentation was modified to minimize habituation, fatigue, and boredom. I presented a task in multiple short runs rather than presenting it in ordered blocks of 'easy', 'medium', and 'hard'. During each run, the three difficulty levels appeared in random order for a very short period. Therefore, instead of changing the stimuli, I could distribute the effect of stimuli habituation across different difficulty levels.

In this experimental study, findings revealed that the participant's attention orientation response, highlighted by the N1 ERP component, exhibited a significant inverse relationship with the cognitive workload. These results agree with those found in the literature (Allison & Polich, 2008; Miller et al., 2011; Takeda et al., 2016) and validated the efficacy of my proposed single-task ERP paradigm to evaluate cognitive workload that was non-sensitive to the habituation effect. These ERP based methods using task-irrelevant tones can be easily adapted to suit rehabilitation settings due to the minimal intrusion of task irrelevant tones and ability to provide actual cognitive workloads associated with a single task, or a dual task. Overall, this experimental study examined the effects of habituation and provided a framework for addressing it. Such a framework can also help researchers looking to validate the efficacy of other objective methods of cognitive workload evaluation such as heart rate, skin temperature, eye blinks, or pupil diameter changes (Kramer, 1991; Tao et al., 2019).

The narrative review **Chapter 3** and the first experimental study **Chapter 4** emphasized the need to investigate how EEG correlates of cognitive workload, such as ERPs, differ at various levels of cognitive workload during rehabilitation. Rehabilitation tasks are typically more dynamic than the task used in the first experimental study where participants were seated on a chair, playing an iPad game while their EEG was recorded. Therefore, we needed to validate the feasibility of implementing our proposed method in more dynamic tasks and since our goal was to implement it in actual clinical settings, we had several discussions with the clinicians to develop a dynamic balance task that was similar to many exercises conducted in rehabilitation.

I conducted an experimental study as my third primary contribution that examined cognitive workload variation in above-mentioned rehabilitation-like task. This rehabilitation-like task included both a balance board and an on-screen game (exergame). Such exergames have been used and validated as a promising method for the rehabilitation of postural stability (Fitzgerald et al., 2010; Lamoth et al., 2012) and balance boards are commonly used in rehabilitation. However, to our knowledge, the cognitive workload of such exergames during rehabilitation have not been measured objectively. Results of my first experimental study, preliminary research, and the narrative review provided the basis on which task-irrelevant single-task ERP-based cognitive workload evaluation method can be implemented for the first time with such rehabilitation-like tasks.

The results of second experimental study confirmed the earlier finding that the attention orienting response (highlighted by the N1 ERP component) decreased with increasing cognitive workload. This study also reported an association of cognitive workload with task difficulty and observable performance during a rehabilitation like task. According to the results of the second experimental study, single-task ERP-based methods are robust in assessing cognitive workload, regardless of the nature of the task (static or dynamic). As the task in the second experiment was more dynamic and closer to an actual rehabilitation task, the positive results demonstrate the usefulness of the single-task ERP-based method for rehabilitation tasks. Therefore, the proposed method can be easily replicated for other rehabilitation task. Furthermore, this method may help clinicians to gain insight into the changes in cognitive workload during rehabilitation tasks which can be used to optimize rehabilitation outcomes. Although future studies are required to validate this method with other rehabilitation tasks, the results of the second experimental study provided the first step towards developing a clinical tool that can evaluate cognitive workload in real-time.

In both experiments, we designed both the static and dynamic tasks to have three distinct levels of difficulty, which were subsequently validated by our proposed ERP-based cognitive workload evaluation method. This highlighted the robustness of the ERP-based methods to evaluate cognitive workload. One important finding from these studies was that the task difficulty significantly modulated only the auditory N100 component as evaluated using a task-irrelevant auditory stimulus. This is consistent with the literature that suggests that the N100 is dependent on working memory resources (Allison & Polich, 2008; Kaseda et al., 1998; Sokhadze et al., 2017; Takeda et al., 2016). Furthermore, a major benefit for the clinical field is the fact that the auditory N100 is reported as unrelated to fatigue in the literature. (Kaseda et al., 1998; Trejo et al., 2005). Considering the auditory N100 component relates exclusively to cognitive workload and does not measure fatigue, it can be considered as the most suitable component for evaluating cognitive workload in rehabilitation.

In summary, the primary aim of this thesis was met with a narrative review and two experimental studies for the purpose of providing a framework for selecting and implementing a robust objective cognitive workload evaluation method in rehabilitation tasks. Some key contributions in achieving this aim are also highlighted in **Table 6.1**.

Table 6.1 Summary of Key findings with research questions

Chapter	Research Questions	Main findings
2	Which evaluation method is best suited for real-life tasks?	Objective cognitive workload evaluation methods should be highly sensitive, less intrusive, diagnostically appropriate, and applicable. EEG/ERP-based methods are best suited for cognitive workload evaluation during rehabilitation.
3	What are the critical factors affecting ERP-based methods evaluate cognitive workload?	ERP-based methods of cognitive workload are affected by both the difficulty and the features of the task. ERP-based methods have high diagnostic power. In an ERP method of measuring cognitive workload, the stimuli should not interfere with the task.
4	Does the single-task ERP paradigm provide an actual measure of cognitive workload?	Single-task event-related potential (ERP) paradigms can provide a reliable index of cognitive workload irrespective of habituation. ERP components corresponding to attention orienting response are modulated by cognitive workload. Task irrelevant stimuli do not interfere with the task and can generate specific ERP components.
5	Is it possible to implement a single-task ERP-based method in rehabilitation settings?	ERP-based methods can assess cognitive workload in rehabilitation settings. A flexible data collection process makes this technique adaptable to diverse rehabilitation settings.

The following sections will discuss the implications of these findings for clinical practice and future research, as well as their strengths and weaknesses.

6.4 Implications for clinical practice

In current clinical practice, the method for providing optimal level of rehabilitation task is by observing performance metrics. Such method is prone to human error and lacks sensitivity to variations in cognitive workload during the task. Therefore, an objective method is needed which can provide cognitive workload variations during the task. Our research has developed and validated a framework for such a method using a rehabilitation-inspired task designed with input from physiotherapists. Based on this method, it may be possible to determine cognitive workload fluctuations during actual rehabilitation tasks which might assist clinical observations in determining task difficulty and cognitive workload of a rehabilitation task.

There is still research that needs to be completed to ensure the proposed method is viable in actual clinical settings, but for now, it can provide clinicians with information about cognitive workload from session to session. Clinicians can, for example, use this method to compare how ERPs changed between sessions in order to understand cognitive workload variation over time. In this thesis, ERP-based methods were shown to have high diagnostic power and can provide information about cognitive workload sources, thus helping clinicians to focus on adjusting only certain aspects of the task (motor or cognitive) to maximize learning. In summary, single-task ERP-based methods can be used to objectively evaluate cognitive workload during rehabilitation-like tasks and I have provided a framework upon which such methods can be further refined. Furthermore, the proposed framework is helpful in informing the development of a real-time tool to monitor cognitive workload during rehabilitation in clinical settings.

6.5 Strengths

Strong preliminary research was conducted to construct the selection criteria for objective cognitive workload evaluation methods best suited for rehabilitation. The selected EEG/ERP based objective cognitive workload evaluation method was critically appraised in a comprehensive review. This review highlighted the high diagnostic power of ERPs and provided a detailed examination of the parameters influencing single-task ERP-based cognitive workload evaluation method. The method to address the effect of habituation of simple auditory tones in single-task ERP-based method was provided for the first time in the literature. This provided method was validated using a rehabilitation-like task which was designed with the help of clinicians and physiotherapists. Overall, this research provided a framework which helps in the selection and implementation of objective methods in rehabilitation.

6.6 Limitations

The proposed method, when incorporated into current clinical settings, can benefit both clinicians and patients. In actual rehabilitation settings, however, there are some limitations associated with the proposed method. One limitation of this method is that it is a novel approach, which needs to be validated against clinically validated tasks of various cognitive workload levels in order to be fully validated. There are two possible ways to address this limitation: either by using a validated behavioural measure of cognitive workload along with the proposed ERP-based method or by using an actual clinical task that can vary cognitive workload levels robustly. Identifying either one of these (the robust behavioural measure or the robust clinical task) is difficult because there is no gold standard for objectively measuring cognitive workload.

Furthermore, from the clinicians' perspective, implementing such a method within clinical decision-making can be time-consuming and cumbersome. We can highlight these limitations through the equipment and methodology used in the proposed method. For the experimental studies, we used state-of-the-art laboratory equipment to validate the proposed method's efficacy, limiting the application of the current method in clinical settings. This limitation can be addressed by looking at the possibility of implementing the proposed method with wireless EEG systems. One major issue with event-related potentials (ERPs) is using an averaging algorithm that limits the implementation of such a method for real-time applications. This limitation can be addressed by using single-trial ERP algorithms. With these algorithms, this research can be further developed in the direction of real-time cognitive workload evaluation.

In addition to the limitations in implementing the proposed method, the method is prone to habituation. For example, the amplitude of the ERP components is affected by both cognitive workload and habituation. In study 1, although we presented the task in a randomized manner to minimize habituation of stimuli during the task, more sophisticated techniques are required to monitor ERP-based methods for habituation effect (source localization). This research is also limited to two laboratory based experimental studies and needs to be tested in actual clinical settings. Moreover, both experimental studies used healthy subjects and need validation across different patient populations.

6.7 Implications for future work

This research provides a framework for implementing an objective cognitive workload evaluation method in actual rehabilitation settings. In this research, a single-task ERP-based method was developed to evaluate cognitive workload in a laboratory experiment involving a rehabilitation-like task. Although this rehabilitation-like task was designed with clinicians' help, the proposed method needs to be validated in actual rehabilitation settings with patients who have a variety of health conditions. There are a few problems with implementing this method in its current form in actual rehabilitation settings, which need to be addressed in the future.

- Future work is recommended in the development of low-cost equipment for data collections. Wireless EEG data collection can help facilitate the implementation of the proposed method in actual rehabilitation settings.

- One possible future development is the update of the algorithm used in current single-task ERP paradigms. Future work should be focused on developing single-trial ERP detection algorithms to help translate this method into a method for evaluating cognitive workloads in real-time.

- In future, ERP-based method could be combined with fNIRS to gain more insights about cortical locations of cognitive workload and how it varies . This combination could provide high temporal and spatial resolution to better understand and interpret cognitive workload.

- We are investigating a prospect using more sophisticated techniques to highlight brain sources involved in cognitive workload variations. One such technique is source localization which provides time/frequency analysis to highlight when certain brain areas were active. This information can help understand the underpinnings of cognitive workload to enhance the proposed single-task ERP method.

The development of the proposed method in the future can help merge this method seamlessly within the current clinical decision-making process. This will be the first step towards developing a clinically validated tool for cognitive workload evaluation that will benefit both patients and clinicians.

6.8 Conclusion

In this thesis, the efficacy of cognitive workload evaluation methods has been explored to objectively evaluate cognitive workload during a rehabilitation task. First selection criteria were constructed from parameters such as intrusion, sensitivity, diagnostic power, mobility, applicability, and reliability to select EEG/ERP based cognitive workload evaluation methods as best suited for objectively evaluating cognitive workload of a rehabilitation task. A comprehensive review of ERP-based cognitive workload evaluation method highlighted the robustness of single-task ERP-based methods and provided information about high diagnostic power of such ERP-based method. This review also highlighted habituation of stimuli as a major limitation of single-task ERP-based cognitive workload evaluation method. To address this limitation, an experimental study provided a task presentation method which could distribute the effect of habituation across different levels of workload. This can help in evaluating actual cognitive workload associated with each level. After validating the efficacy of single-task ERP-based method a second experimental study used the same task presentation with a rehabilitation-like task. This task was designed with the help of clinicians and physiotherapists and positive results of the second experimental study highlighted the proposed method as best suited to evaluate cognitive workload of actual rehabilitation tasks.

In its current form, the proposed method can provide information about cognitive workload variation during the task which can aid clinical observations and assist clinicians in their decision-making process. In addition to supporting clinicians in decision-making, this can help patients recover more quickly (performing rehabilitation task at challenging level). However, future work is required to seamlessly merge the proposed cognitive workload evaluation method in actual rehabilitation settings. Overall, the present research provides a framework on which an objective method of assessing cognitive workload can be implemented in rehabilitation paradigms, which can then be used to develop a real-time clinical tool to assess cognitive workload during rehabilitation to facilitate both patients and clinicians.

6.9 COVID-19 Impacts

COVID 19 has negatively impacted the timeline of my PhD. At the end of February 2020, I had completed the design of my second experimental study, published two papers, and was on track to submit my PhD in August 2020. When the first lockdown in Auckland occurred, I was about to start collecting data for my second study, thus delaying my data collection by three months. In August 2020, after receiving a green signal from the government, I began my data collection. However, due to fear of COVID, recruitment was very slow with limited students both on and off campus. In Auckland, the recruitment process was further slowed by safety measures and frequent changes in lockdown levels. Despite all this chaos, I was able to complete my data collection process by October 2020.

As soon as possible, I began working on data processing, but a family emergency forced me to visit my home country in November 2020. As an international PhD student my timetable was most affected by the still-existent border restrictions. After trying for six months, I got my critical visa in August 2021, as part of 1000 returning international students. My biggest obstacle after securing my visa was finding a place in MIQ due to the limited spaces. After struggling for almost four more months, I was able to secure a spot at MIQ for 27th of February 2022. I was working on my PhD during my attempts for visa and MIQ but was repeatedly delayed due to the limited access to my lab and computer at AUT. However, thanks to my supervisors' constant support and efforts, I published my third research paper and started combining the entire thesis. I planned a date for my thesis submission in April 2022 in discussion with my supervisors.

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Appendices

Appendix A: Participant Information Sheet (Study 1)

Date Information Sheet Produced:

11 06 2019

Project Title

EEG correlates of task difficulty: Development of an objective measure of cognitive workload

Kia ora, Talofa lava and hello, my name is Usman Ghani, and I am a PhD student at AUT. I am conducting an experimental study to evaluate cognitive workload as a part of my PhD. You are invited to take part in this study.

What is the purpose of this research?

In neurological rehabilitation paradigms, a clinician prescribes a rehabilitation task to the patient and goal of this task is to be challenging enough so it can help and motivate a patient in the rehabilitation process. Thus, finding the challenge point is the main concern to maximize recovery in neurological rehabilitation. If the challenge point is not found, and the assigned task is either too easy or too difficult for the patient can impede the rehabilitation progress.

In current neurological rehabilitation paradigms, the challenge point is found using a patient's feedback or a clinician's observation. These measures cannot give any information regarding brain activity while performing the task. So, there is a pressing need of an objective measure of brain activity to find the challenge point of a task. This real-time evaluation of challenge point can help clinicians to prescribe the rehabilitation task at a challenging level.

This research aims to identify and optimize the correlates of brain activity using electroencephalogram (EEG). These correlates will help in devising a clinical tool to measure and find the challenge point in rehabilitation paradigms Findings of this study will act as the base for further studies and can be used in publications and presentations.

How was I identified and why am I being invited to participate in this research?

Your participation in this study is voluntary, and you will contact me if you are interested. You may be eligible for this study if you meet the following entry criteria:

- Aged between 20 to 30 years,
- Do not have any neurological disorders,
- Do not have a skull fracture or other known skull defects,
- Have not had a head injury or concussion within the last six months,

- Do not have a pacemaker, intracardiac lines, artificial heart valve containing a conductive material, and cranial-facial reconstruction or metal implants in the head or hand region.

We will be recruiting 25 people to participate in the study.

How do I agree to participate in this research?

Your participation in this research is voluntary (it is your choice) and whether or not you choose to participate will neither advantage nor disadvantage you. You are able to withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, removal of your data may not be possible.

What will happen in this research?

You will be contacted by us to make an appointment to attend the laboratory at the Health & Rehabilitation Research Institute, AUT North Campus, Akoranga Drive, Northcote. This study involves participating in 1 session which will be one hour long. This session involves recording your brain activity while performing a primary task which is a game called High-roller on an iPad. It has three distinct levels (Easy, medium and hard). This game is shown in Figure 1.

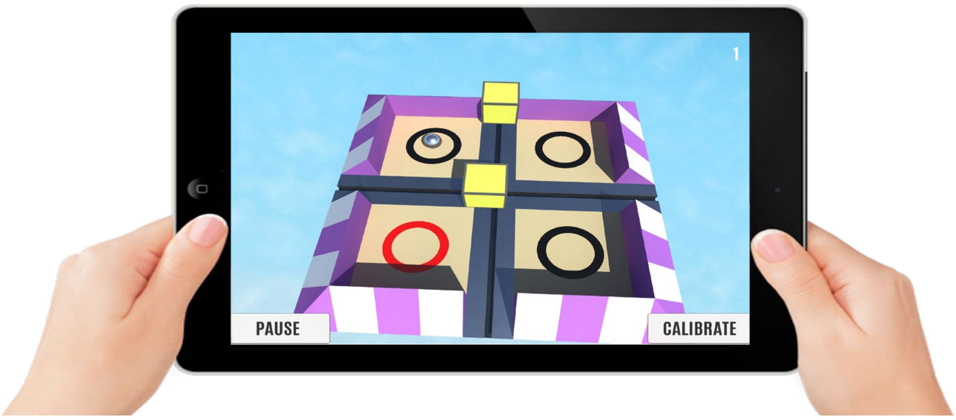


Figure 1 High roller (Game designed by Exsurgo)

Brain activity will be recorded using non-invasive electroencephalogram (EEG) technique while playing this game. This is a safe and painless technique that involves the researcher adjusting the EEG cap on the head and then inserts gel into the electrodes for proper connection with the skull. Figure 2 highlights the setup of EEG for recording brain activity in this study.

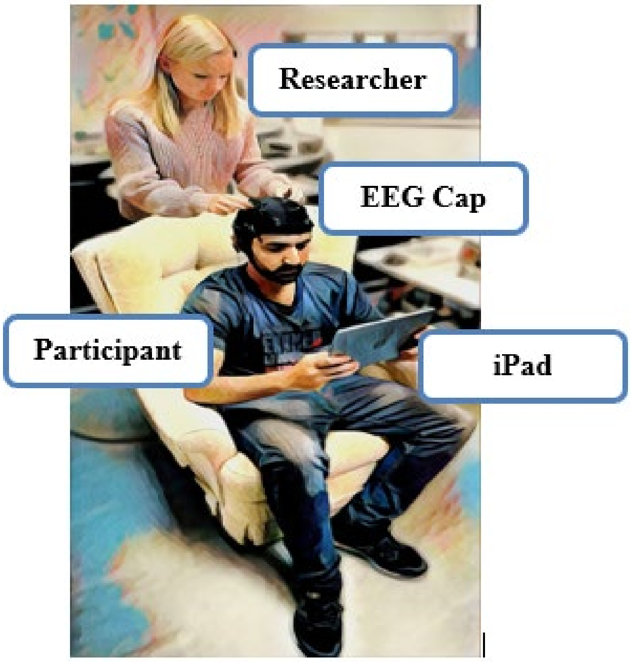


Figure 2 EEG recording setup

The Electroencephalography (EEG) cap used in this study has electrodes attached to it to record your brain activity during the session. A conductive gel is placed in each of the electrodes allowing a good EEG signal to be detected by the computer. The Electrode cap used to collect EEG is shown in Figure 3.

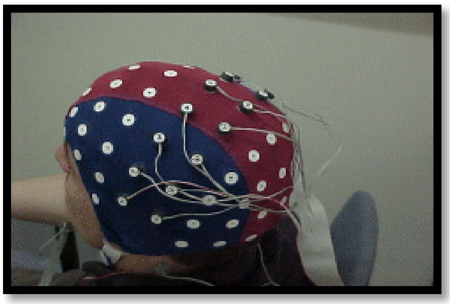


Figure 3 EEG cap

If you are interested in taking part in the study, contact the primary researcher. This study uses a usual clinical EEG system which is safe to use.

There will be a single session for each participant which will last for approximately one hour. You will be asked to play the game for eight runs of six minutes each. Every run will have three distinct levels (two minutes for each phase). There will be a one-minute break after every run.

What are the discomforts and risks? How will these discomforts and risks be alleviated?

There is a small chance that the procedures being used in this study may make some people anxious. We will minimize this chance by making sure you are fully informed about what to expect before any procedure. We will monitor how you are feeling throughout each procedure, and you can stop the session at any stage. There can be some discomforts associated with the procedure.

The skin behind the right ear will be exfoliated and wiped with an alcohol wipe before the reference electrode can be applied. This can cause a temporary stinging sensation and may cause minor temporary skin reddening.

The EEG uses a conductive gel. A very small amount of gel will be applied to each electrode. This gel is made up of 'Table Salt', thickening agent and some preservatives. It is completely harmless. However, after removing the Cap, small patches of the dried gel are left in your hair which can be removed by a usual hair wash.

A straw like metal probe will be used to adjust the hairs in the cap to expose the scalp then the gel will be inserted into electrode compartments of the EEG cap.

What are the benefits?

There are no direct benefits to you. However, by taking part in this study, you are acting, as co-researcher and your contribution will help in a study which is a part of my PhD and aim my PhD is to develop a prototype method which will assist clinicians in neurological rehabilitation paradigms. You will also have the experience of participating in a modern research laboratory project.

What compensation is available for injury or negligence?

In the unlikely event of a physical injury as a result of your participation in this study, rehabilitation and compensation for injury by accident may be available from the Accident Compensation Corporation, providing the incident details satisfy the requirements of the law and the Corporation's regulations.

How will my privacy be protected?

Your confidentiality will be maintained in the following ways. Results will be identified by a code number only. Researchers will only have access to coded data, which will exclude your identity. All results will be pooled, so no names or any material that could identify you, will be published or presented. Consent forms are locked away in a separate location from the data so that no association can be made between the results and the consent forms. After ten years, this data will be destroyed.

What are the costs of participating in this research?

The cost to you is your time and travel. This would be a one-hour session, excluding your travel time. Supermarket vouchers will be provided on a visit to partially compensate for your time and to assist with travel costs incurred for traveling to and from the laboratory.

What opportunity do I have to consider this invitation?

You are encouraged to take time to consider this invitation and to discuss it with family/whanau. You will have two weeks to decide after receiving this information sheet. If you have any questions, please feel free to contact one of the researchers listed below. If you would like to be considered for the study, please respond to this invitation within two weeks.

Will I receive feedback on the results of this research?

Yes. If you wish, a copy of your results and a summary of the overall findings will be sent to you when the study is completed. It is usual for there to be a substantial delay between the time of your participation and the time of receiving these results.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, *Dr. Denise Taylor,* denise.taylor@aut.ac.nz *921 9680*

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, *Kate O'Connor, ethics@aut.ac.nz, 921 9999 ext 6038.*

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details

Primary Researcher:	Usman Ghani Health & Rehabilitation Research Institute AUT University Private Bag 92006 Auckland 1142 921 9494 usman.ghani@aut.ac.nz

Supervisor Contact details:

Project Supervisor	Dr Denise Taylor Health & Rehabilitation Research Institute AUT University Private Bag 92006 Auckland 1142 921 9680 Denise.taylor@aut.ac.nz

Appendix B: Poster of study 1

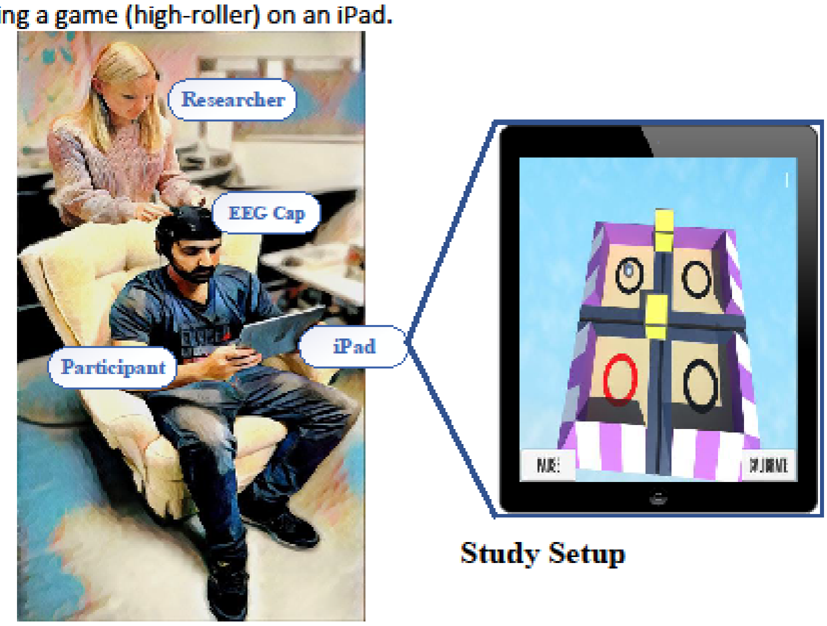
AUT
TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Appendix 2

VOLUNTEERS REQUIRED FOR A PhD RESEARCH PROJECT

Are you interested in participating in a modern laboratory research project aiming to develop a new prototype method for evaluating and indexing cognitive workload?

We are looking for **healthy participants with age limit of 20 to 30 years** to participate in a study. In this study brain signals will be recorded via non-invasive electroencephalogram (EEG) method while playing a game (high-roller) on an iPad.



Study Setup

The EEG system interprets brain signals whilst participants play the game. Amplitude of certain potentials in the EEG changes when the difficulty of the game is increased. **The purpose of this study is to look at this change in amplitude to evaluate cognitive workload.** Testing will take approximately **one hour** of your time at the **AUT University North Shore Campus.**

Contact:
Usman Ghani
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09 921 9494

Contact: Usman Ghani usman.ghani@aut.ac.nz 09 921 9494
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Appendix C: Ethics approval letter (Study 1)

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

17 June 2019

Denise Taylor
Faculty of Health and Environmental Sciences

Dear Denise

Re Ethics Application: **19/97 EEG correlates of task difficulty: Development of an objective measure of cognitive workload**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 17 June 2022.

Standard Conditions of Approval

1. A progress report is due annually on the anniversary of the approval date, using form EA2, which is available online through http://www.aut.ac.nz/research/researchethics.
2. A final report is due at the expiration of the approval period, or, upon completion of project, using form EA3, which is available online through http://www.aut.ac.nz/research/researchethics.
3. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form: http://www.aut.ac.nz/research/researchethics.
4. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
5. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.

Please quote the application number and title on all future correspondence related to this project.

AUTEC grants ethical approval only. If you require management approval for access for your research from another institution or organisation, then you are responsible for obtaining it. You are reminded that it is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard.

For any enquiries, please contact ethics@aut.ac.nz

Yours sincerely,

K O'Connor

Kate O'Connor
Executive Manager
Auckland University of Technology Ethics Committee

Cc: usman.ghani@aut.ac.nz; nada.signal@aut.ac.nz; Imran Niazi

Appendix D: Recording protocol for study 1

ERP Recording Protocol for study 1

- Lab/technical set up prior to participant arriving
- Participant Introduction and consent process
- Preparing participant
- Data collection

Lab/technical set up prior to participant arriving

Switch on:

- **Computer 1** → Tone Generation
- **Computer 2** → EEG Recording

While running **Computer 1**

- Connect USB cable from **Computer 1** to back of **Red CED Board**
- Open MATLAB and set path to UsmanStudy → ToneGeneration
- Run runToneWithExtTrig.m and enter the required duration of recording.

After setting up computer move to **Computer 2**

While running **Computer 2**

- Connect **Nuamps** USB lead into **Computer 2**
- Connect YELLOW sync 1 lead from **Nuamps** to a double connecter that will be connected to **Red CED Board** Outputs 0
- To transfer the 'CUE' into EEG data, connect a short cable from the other side of the double connector in **Red CED Board** Outputs 0 to the **Blue CED Board** Inputs 3
- Connect USB from back of **Red CED Board** into **Computer 2**
- TURN ON **Blue CED Board**
- TURN ON **Red CED Board**

After setting up all the connections on both computers

While running Computer 2

- Open **SCAN 4.5 Launchpad**
- Click **Acquire**
- File > load Set Up > select **UsmanStudy1**
- Acquisition > Impedance
- Push small ‘Z’

Participant Introduction and consent process

Following recruitment, participants will be scheduled for data collection in lab at a time convenient to them. After lab setup and orientation following protocol will be followed for each participant.

- Have you read the **Participant information sheet**? Do you have any confusion regarding this session?
- We will be recording your brain activity (EEG) while playing a game called high roller. So let me show you both the game and the equipment that we will be using for this session.
- This is the EEG cap that I will adjust on your head and you can see there are numerous electrodes on the cap to record signals. This cap will be connected to this amplifier which will amplify the signal and send it to the computer.
- To make better connection of electrodes and the head surface I will be using this salt based gel which I will insert in the electrodes using a syringe that has blunt needle. You can see this needle is not pointy.
- This is the game that you will be playing. So it has three different levels of difficulty and your goal is to avoid the moving obstacles and achieve as many points as you can in a given time. Each time you move the sphere to highlighted region you will get one point and if you hit the obstacle it will deduct one point.
- As you know this is a one hour session which will be divided into eight trials of six minutes each. Every six minute trial has three levels (2 minutes each). After every level you will be asked to rate the difficulty using a scale that will be presented on screen for each level (0 for easy and 10 for hard)

After explaining the trial and session we will move to the next part.

- I would like to ask you some personal information for study records and to ensure that you meet the criteria of the study.
- Complete screening checklist

This document is a consent form saying that you are happy to participate in the research and outlining your rights as a participant. Please read the form.

- Is there anything else you would like me to explain or clarify?
- Do you have any other questions?

You should also know that at any time you may withdraw from the study, no questions will be asked.

- Would you like to receive a summary of the research?
- Would you like to be contacted about the possibility of participating in future studies undertaken by the neurophysiology laboratory of the Health and Rehabilitation Research Institute of AUT University?
- Are you happy to take part in the study?

Please sign this consent form.

Preparing participant

Participant will be seated in a chair in a relaxed position

- Prepare skin behind ear by rubbing with cotton bud and Nuprep abrasive gel --- Wipe with alcohol wipe and allow to dry.
- Apply surface electrode behind right ear on mastoid.
- Position EEG Quick-cap on participant's head and ensure cap is tight and doesn't pucker.
- The CZ electrode should be placed midway between the nasion and the inion in the sagittal plane, and midway between each tragus in the coronal plane.
- Measure the distance from nasion to cap, tape down and record distance on data collection sheet.
- Connect **A2 blue lead** from Numpas to electrode behind the ear
- Connect EEG cap plug to Nuamps
- Use the blunt needle to apply gel to electrodes start with GND …FP1, FP2, C4, CZ, C3, P4, PZ, P3, F4, FZ, F3.
- Gently rotated to lightly abrade the skin with the aim of maintaining impedance below 5kΩ the blunt needle is

- Check impedance is below 10% for each electrode (dark blue colour on Aquire)

When everything is in place and all set to start.

- Start a check Run to see if all the codes and equipment is working.
- Enter the speed of boxes in the game
- Tablet angle is calibrated by the participant.

RUN the Codes

Data Collection

Running above codes will keep on saving data at defined location in Computer 2.

- Get **.CNT** files from Computer 2 (There files contain cued data).
- Get the channel file **NuAmps40.asc**

After getting all the files from computer 2. We will follow a pipeline designed to extract ERP components. This pipeline has three steps (Step Zero, Step I, and Step II)

- **Step Zero** → change the name of **CNT** and convert it into different format for EEGLAB. Load channel file (**NuAmps40.asc**) into setup folder
- **Step I** → Gives you marked (with cue) channel data in. mat format. It also gives channel spectrum and histogram.
- **Step II** → Works on EEGLAB give you options to visually exclude a channel. It excludes epochs by visual inspection (Too noisy). It runs ICA and gives the components graphs. It also gives you option for removing data based on ICA components. It also plots averaged ERPs for each channel. It again saved the results for visualization.

Appendix E: Consent form for study 1

Consent form

Project title: **EEG correlates of task difficulty: Development of an objective measure of cognitive workload.**

Project Supervisor: **Prof. Denise Taylor**

Researcher: **Usman Ghani**

○ I have read and understood the information provided about this research project in the Information Sheet dated 11 06 2019.

○ I have had an opportunity to ask questions and to have them answered.

○ I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.

○ I understand that if I withdraw from the study then I will be offered the choice between having any data or tissue that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings have been produced, removal of my data may not be possible.

○ I am not suffering from a neurological disorder, have not had a head injury in last six months, don't have a hearing problem and don't have a pacemaker or any metal implants in my head or trunk region.

○ I agree to take part in this research.

○ I wish to receive a summary of the research findings (please tick one): **Yes**○ **No**○

Participant' signature : ....

Participants Name : ....

Participant's Contact Details (if appropriate):

……………………………………………………………………………………………..

Date : ………………………………

Approved by the Auckland University of Technology Ethics Committee on type the date on which the final approval was granted AUTEC Reference number type the AUTEC reference number

Appendix F: Participant Information Sheet (Study 2)

Participant Information Sheet

Date Information Sheet Produced:

2 06 2020

Project Title

EEG correlates of task difficulty: Development of an objective measure of cognitive workload

An Invitation

Kia ora, Talofa lava, and hello, my name is Usman Ghani, and I am a Ph.D. student at AUT. I am conducting an experimental study to evaluate cognitive workload as a part of my Ph.D. You are invited to take part in this study.

What is the purpose of this research?

The goal of neurological rehabilitation paradigms is to assign a programme which is challenging enough to help and motivate a patient in a rehabilitation process. Thus, finding the challenge point is the primary concern to maximize recovery in neurological rehabilitation. If the challenge point is not found and the programme is assigned, which is either too easy or too difficult for the patient, it will result in cognitive overload or cognitive under-load.

In current neurological rehabilitation paradigms, the challenge point is found using subjective measures such as patient's feedback and clinician's observation. These measures cannot give any information regarding brain activity while performing the task. So, there is a pressing need for an objective measure of the brain activity to evaluate cognitive workload while performing the rehabilitation task. This real-time evaluation of cognitive workload in rehabilitation paradigms can help clinicians to deal with the concerns of cognitive overload and cognitive under-load.

This research aims to identify the EEG correlates to measure cognitive workload. The output of this research will be a proof-of-concept and early prototype of a clinical tool for measuring cognitive workload in rehabilitation tasks. The findings of this study may be used in publications and presentations.

How was I identified and why am I being invited to participate in this research?

Your participation in this study is voluntary, and you will contact me if you are interested. You may be eligible for this study if you meet the following entry criteria:

- Aged between 20 to 30 years,
- Do not have any neurological disorders,
- Do not have a skull fracture or other known skull defects,

- Have not had a head injury or concussion within the last six months,
- No musculoskeletal injury
- No vestibular impairment

Do not have a pacemaker, intracardiac lines, artificial heart valve containing a conductive material, and cranial-facial reconstruction or metal implants in the head or hand region.

We will be recruiting 24 people to participate in the study.

How do I agree to participate in this research?

Your participation in this research is voluntary (it is your choice), and whether or not you choose to participate will neither advantage nor disadvantage you. You are able to withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, the removal of your data may not be possible.

What will happen in this research?

You will be contacted by me to make an appointment to attend the laboratory at the AX building, AUT, Northshore. This study involves participating in 1 session, which will be one hour long. This session involves recording your brain activity while performing a primary task. This primary task will be presented as a custom game using a balance board, a mobile, and a computer/LED.

This custom game is designed for an android mobile, which will be placed inside a compartment in a balance board. This balance board has an angle of tilt, and you can tilt the board by tilting yourself in a certain direction. The game uses mobile sensors to move the ball in the desired direction. You will try to score the highlighted goal by tilting yourself on a balance board. As the board tilts, mobile will tilt in that direction, so as the ball in the game. The complete setup is shown in figure 1A, and figure 1B highlights the gameplay on an android device.

Brain activity will be recorded using a non-invasive electroencephalogram (EEG) technique while playing this game. This is a safe and painless technique that involves the researcher adjusting the EEG cap on the head and then inserts gel into the electrodes for proper connection with the skull. Figure 2 shows the EEG cap from OpenBCI which will be used in this study.

The complete preparation setup for EEG recording is shown in figure 3.

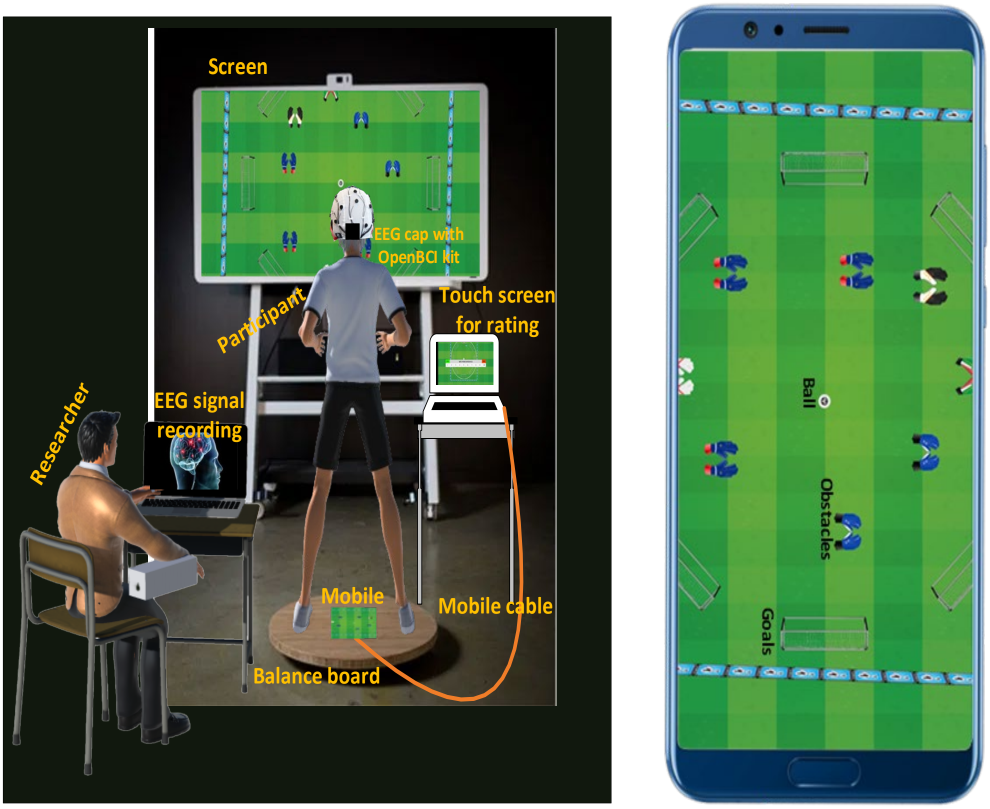


Figure 1 A) shows the complete study setup. 1B) shows the gameplay on an android device

Figure 2 shows EEG Cap from OpenBCI

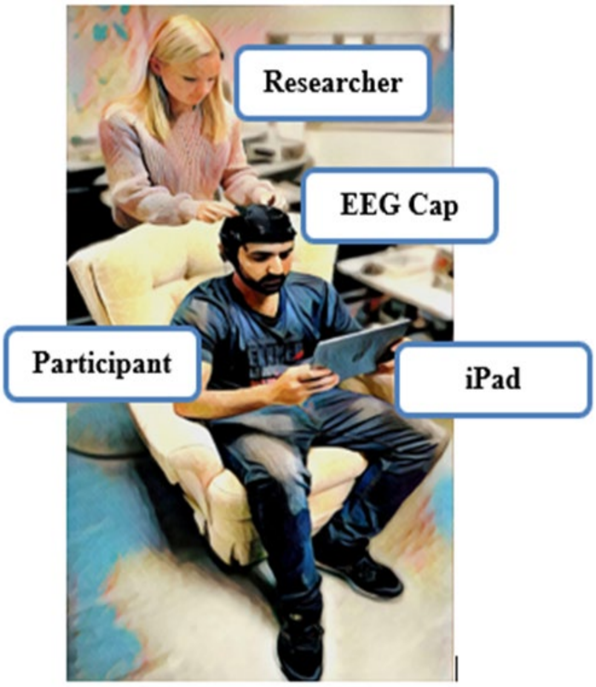


Figure 3 EEG recording preparation

If you are interested in taking part in the study, contact the primary researcher. In this study, all the safety guidelines regarding COVID-19 will be followed. The EEG system used in this study is from the usual clinical practice, and it is safe to use.

There will be a one-hour session per participant, and this session will contain Eight separate runs of 7.5 minutes each. In every run, three difficulty levels (easy, medium, and hard) will be presented in a random order where each level lasts for 90s blocks. There will be a 50s break after each level and an 80s break after each run. This presentation of task for one run is shown in figure 4 where task is presented for 270s with 180s of break in each run.

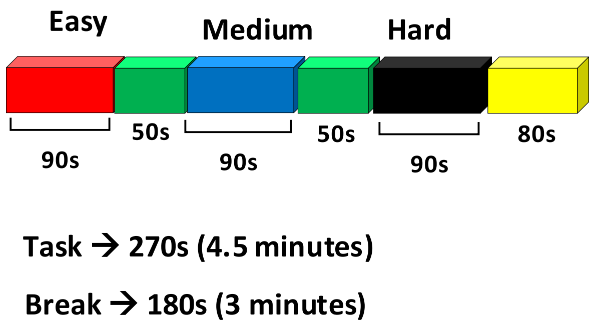


Figure 4 Presentation of task within single run

What are the discomforts and risks?

There can be some discomfort associated with the procedure.

1. The skin behind the right ear will be exfoliated and wiped with an alcohol wipe before the reference electrode can be applied. This can cause a temporary stinging sensation and may cause minor temporary skin reddening.

2. The EEG cap uses a conductive gel. A tiny amount of gel will be applied to each electrode in the cap. This gel is made up of 'Table Salt', thickening agent, and some preservatives. It is entirely harmless. However, after removing the EEG cap, small patches of the dried gel are left in the hair, which can be removed by a usual hair wash.

3. A blunt needle will be used to insert the gel into electrode compartments of the EEG cap. This needle comes in contact with the head and slightly abrades the skin but does not break into it. A blunt needle is just like a straw, and it is not pointy.

How will these discomforts and risks be alleviated?

We will minimize this chance by making sure you are fully informed about what to expect before any procedure. We will monitor how you are feeling throughout each procedure, and you can stop the session at any stage. Aloe Vera gel will be used in case you feel any discomfort behind your ear.

What are the benefits?

There are no direct benefits to you. However, by taking part in this study, you are acting, as co-researcher and your contribution will help in a study which is a part of my Ph.D. and aim my Ph.D. is to develop a prototype method which will assist clinicians in neurological rehabilitation paradigms. You will also have the experience of participating in a new research laboratory project.

What compensation is available for injury or negligence?

In the unlikely event of a physical injury as a result of your participation in this study, rehabilitation and compensation for injury by accident may be available from the Accident Compensation Corporation, providing the incident details satisfy the requirements of the law and the Corporation's regulations.

How will my privacy be protected?

Your confidentiality will be maintained in the following ways. Results will be identified by a code number only. Researchers will only have access to coded data, which will exclude your identity. All results will be pooled, so no names or any material that could identify you, will be published or presented. Consent forms are locked away in a separate location from the data so that no association can be made between the results and the consent forms. After ten years, this data will be destroyed.

What are the costs of participating in this research?

The cost to you is your time and travel. This would be a one-hour session, excluding your travel time. Supermarket vouchers will be provided on a visit to partially compensate for your time and to assist with travel costs incurred for traveling to and from the laboratory.

What opportunity do I have to consider this invitation?

You are encouraged to take the time to consider this invitation and to discuss it with family/whanau. If you have any questions, please feel free to contact one of the researchers listed below. If you would like to be considered for the study, please respond to this invitation within one month.

Will I receive feedback on the results of this research?

Yes. If you wish, a copy of your results and a summary of the overall findings will be sent to you when the study is completed. It is usual for there to be a substantial delay between the time of your participation and the time of receiving these results.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, *Dr. Denise Taylor, denise.taylor@aut.ac.nz 921 9680*

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, *ethics@aut.ac.nz*, (+649) 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details:

Primary Researcher:

Usman Ghani
Health & Rehabilitation Research Institute
AUT University
Private Bag 92006
Auckland 1142
921 9494
usman.ghani@aut.ac.nz

Project Supervisor Contact Details:

Project Supervisor

Dr Denise Taylor
Health & Rehabilitation Research Institute
AUT University
Private Bag 92006
Auckland 1142
921 9680
Denise.taylor@aut.ac.nz

Approved by the Auckland University of Technology Ethics Committee on *type the date final ethics approval was granted*,

AUTEC Reference number *type the reference number*.

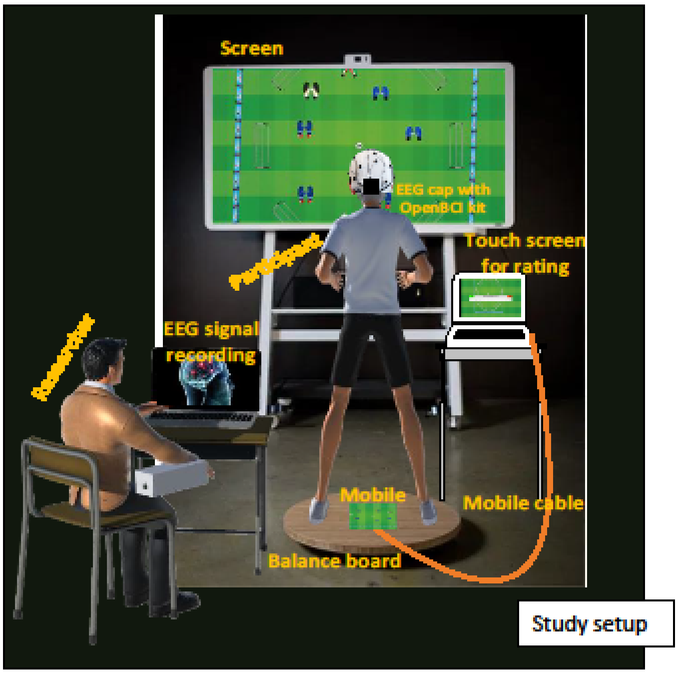
Appendix G: Poster of Study 2

VOLUNTEERS REQUIRED FOR A PhD RESEARCH PROJECT

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Are you interested in participating in a recent laboratory research project aiming to develop a new prototype method for evaluating and indexing cognitive workload?

We are looking for **healthy participants with an age limit of 20 to 30 years** to participate in a study. In this study, brain signals will be recorded via a non-invasive electroencephalogram (EEG) method while playing a game using a balance board and a mobile.



The EEG system interprets brain signals while participants play the game. The amplitude of specific potentials in the EEG changes when the difficulty of the game is increased. **The purpose of this study is to look at this change in amplitude to evaluate cognitive workload.** Testing will take approximately **one hour** of your time at the **AUT University North Shore Campus.**

Contact:
Usman Ghani
usman.ghani@aut.ac.nz
09 921 9494

Contact: **Usman Ghani** usman.ghani@aut.ac.nz 09 921 9494
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Appendix H: Ethics approval letter (Study 2)

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

4 August 2020

Denise Taylor
Faculty of Health and Environmental Sciences

Dear Denise

Re Ethics Application: **20/179 Cognitive workload evaluation during a gamified balance task**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 4 August 2023.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard and that all the dates on the documents are updated.

AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: usman.ghani@aut.ac.nz; nada.signal@aut.ac.nz; Imran Niazi

Appendix I: Sample size calculations

Appendix 5

Sample Size Calculation

Project title:	**EEG correlates of task difficulty: Development of an objective measure of cognitive workload.**
Project Supervisor:	**Professor Denise Taylor**
Researcher:	**Usman Ghani**

The power calculation for this study is based on the mean effect sizes and standard deviations from a previous study (AUTEC 19/97). The preliminary analysis includes effect size calculation using readings of amplitude changes of the N1 component. In this study, repeated measures analysis of variance test was used with level (easy, medium, and hard) and the amplitude of the N1 component as the main terms. This statistical analysis revealed a significant difference between levels for N1 component $F(2,196) = 4.94$, $p<0.01$, $\eta^2 = 0.2$. We used Gpower to calculate effect size based on the value of eta square. Other parameters used for sample size calculations using repeated measures ANOVA are shown in Table 1.

Table 1 Sample size Calculation

Parameters	Values
Eta squared (η^2)	0.2
Effect Size(f) based on (η^2)	0.5
Error Probability (α)	0.05
Power ($1-\beta$ error probability)	0.8
Number of measurements	199
Number of groups	3
Calculated Sample Size	**24**