Universiteit Utrecht

Master Thesis Human-Computer Interaction

Measuring the effects of presence and tempo of background music on cognitive load during digital tasks using eye tracking

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Preface

First of all, **please open this document in a PDF viewer - preferably Adobe Acrobat Reader**. With other software or browsers, I cannot guarantee that all the media (images, GIF's, hyperlinks, etc) will work.

I want to firstly thank my supervisor Christof van Nimwegen for his guidance, continuous and valuable feedback, and support. Thank you to the second reader, Frans Wiering, for reviewing and assessing this thesis. Thanks to all the participants for making time and providing me with their useful insights!

This thesis has meant a lot to me. Not only did I find the topic truly enjoying to write about and to experiment with, but I have also learned much from the entire process. From setting up and using the eye tracking equipment to writing the Python script for data analysis, conducting statistical analysis, and presenting the results. Perhaps I may not continue working in the academic world, but I'm really drawn to this field of science.

Finally, thanks to my housemates for understanding my reclusive behaviour in my own room to study, listening to the good and bad stories, not complaining about my increasingly bad mood as deadlines approached, and cheering me up when needed. Thank you! From now on, I'm truly here.

I hope you find this thesis both interesting and enjoyable.

Mike van Gils

Abstract

This researches contributes to our understanding of the effects of the presence and tempo of background music on our cognitive load during digital tasks, using eye tracking to provide a measurement. The modern availability and accessibility of music streaming during daily low-demanding and high-demanding attention tasks, asks for more understanding of its effects on our cognitive performances. Earlier literature showed both positive and detrimental effects of music on our physical and mental health, but the exact influence on cognitive load during attention-demanding tasks stays under-explored. Scientific theories suggests that background music, as extraneous load, could increase our cognitive load, with the potential to harm our performance.

Using a between-subjects experimental design to compare a control group to fast tempo and slow tempo background music conditions, the literature gap is attempted to be closed. Eye tracking data was collected to measure fixation duration, fixation rate, and pupil size as indicators of cognitive load compared to subjective measurements. Both presence and tempo of background music was expected to have significant influence on these eye behaviour variables, with fast tempo music having a greater effect.

The results and discussion of this study, therefore, attempted to shine some light on how background music is related to (perceived) cognitive load, providing further insight into HCI and our societal behaviour concerning listening to music. By discussing the dual role of background music as motivator and disturber, this research aimed to add some understanding to how music as extra stimuli affects our digital task performance.

Contents

Chapter 1

Introduction

Where vinyl, CD's and cassettes conquered the music industry in the last decades, the internet has provided a fertile environment for artists and publishers to expand their reach. The dematerialization of music has resulted in an explosive boost in availability, in a way that it has become ubiquitous. Not only are we exposed to music in a passive way such as during shopping in the grocery store, but the phenomenon of *streaming* allows us to listen to almost every single piece of music at almost every place in the world. Music streaming services such as Spotify, Apple Music, or Amazon Music have grown to more than a billion active users in total, of which half a billion are paid subscribers (Mulligan, 2022). The average Dutchman even spent 152 minutes every day listening to music in 2018 (The Statistical Portal, 2019).

This online availability of music allows for *on-demand* streaming (i.e. listen to selected music at his or her schedule's convenience) with over 75% of the Americans confirming they actively choose to listen to music (Nielsen, 2015). The modern technology allows people to stream music in any place at any time while performing all kinds of tasks, whether it's working, studying, or more low-demanding attention tasks such as scrolling through social media or easy chores at home.

The fact that people tend to listen to music during these tasks is reasonable. Music has shown to be beneficial for both our physical and mental health in science (Rebecchini, 2021). As a positive factor in sports, music stimulates and synchronizes our tempo and therefore motivates us in the physical exercises (Karageorghis and Terry, 1997). The advantages of music for our mental health are in turn more related to its relaxing character. In science, music is being used as assistants to improve sleep quality (De Niet et al., 2009) or as a helpful tool in anxiety therapy and for positive physiological responses (Davis and Thaut, 1989).

However, there tends to be a downside of music. Music won't be quickly seen as a rough task itself, but it remains an extra load for our brain to process. During the day our brain has limited capacity for tasks and other stimuli seeking for our attention. Exceeding this cognitive capacity to process information, can result in an overload of stimulation. This *cognitive overload* can affect our performance with a drop of memory, increased stress levels, and lack of concentration - but also more social effects such as social tension with colleagues or family and friends (Kirsh, 2000).

The connection between music, our mental state and cognition is however quite complicated. Their intersection is dependent on many aspects of both music and more importantly the task that is being performed while listening to this music. On the one hand, music can be listened to during low-demanding attention tasks such as household chores. In that case people often tend to actively choose to listen as a distraction or to make the situation more comfortable. But on the other hand, nowadays people also are exposed to music during more attention-demanding tasks such as working or studying, requiring far more concentration. In this case, the music is being stimulated mainly as a passive background music. The question then rises whether the benefits of music remain or if they are being overtaken by the downsides. Moreover, the characteristics of music have their own stake in this whole connection. Whether it's the lyrics, language, emotion of tempo – all are involved in the final effects of music on the execution of these tasks (Sousou, 1997).

In earlier literature, the effects of music have been examined thoroughly as will be discussed in this paper's theoretical sections. However, the connection between music, cognitive load, and our attention during (digital) tasks has not been researched clearly yet due to the possible variance in kinds of tasks and kinds of music. This research therefore aims to contribute to this gap in science. Methodologically, cognitive load is often being measured with eye tracking; a sensory practice to objectively capture eye movements and other related variables such as blinking behaviour and pupil size. Especially in the field of *Human-Computer Interaction* (HCI), eye tracking is a popular methodology used for web design studies, marketing techniques, and psychological practices.

Therefore, in this research, eye tracking will be used as a measurement of cognitive load when subjected to music during digital tasks. The appliance of eye tracking within the context of background music and cognitive load is fresh in this field of science and raises the question whether it can be used as a reliable measurement. Due to this exceptional broadness of music, this paper will narrow down its focus in terms of conditions and variations being discussed in the methodology section.

Chapter 2

Theoretical Framework

2.1 Cognitive Load in HCI

Cognition includes all the mental activities of a human (Harvey et al., 2005). It refers to our mental processes needed to gather, save, and use information to execute both easy, reflective, and specialized tasks (Gudivada et al., 2019; Norman, 1993). Key components of cognition range widely from perception, attention, and memory to problem-solving and decision-making (Cabeza and Nyberg, 1997; Kelly et al., 2020). With the *Cognitive Load Theory*, Sweller et al. (1998) laid the foundation of an instructional design theory claiming that our working memory is (1) limited in capacity and duration in terms of processing information, and (2) responsible for storing relevant information in the unlimited long-term memory. Although this theory is initially based on and meant for the process of learning, it has spread its use firmly to HCI in general in context of *usability*, *user experience* and *interface design* (Hollender et al., 2010).

The cognitive load theory consists of three components: (1) intrinsic load, (2) extraneous load, and (3) germane load (Sweller et al., 1998). Intrinsic load describes the active processing difficulty of a specific instruction or task. An example of intrinsic load in HCI could be learning how to use a complex software interface when it's completely new for the user. Extraneous load, in contrary, is not directly relevant or contributing to the task, but still exposes subjects to stimuli to process. In web design, irrelevant and distracting graphics are increasing the extraneous load (Merriënboer and Ayres, 2005). Lastly, germane load is the effort devoted to handle the storing of long-term information, making mental schemas (Sweller et al., 1998). This theory by Sweller et al. is especially relevant for this research since it distinguishes between the nature of different kinds of stimuli. By specifying the three types of sources (intrinsic, extraneous, and germane) and how they relate to one another, this theory allows for hypothesizing the potential effects of music on different kinds of digital tasks. The interplay of intrinsic, extraneous and germane load is visualized in Figure 2.1.

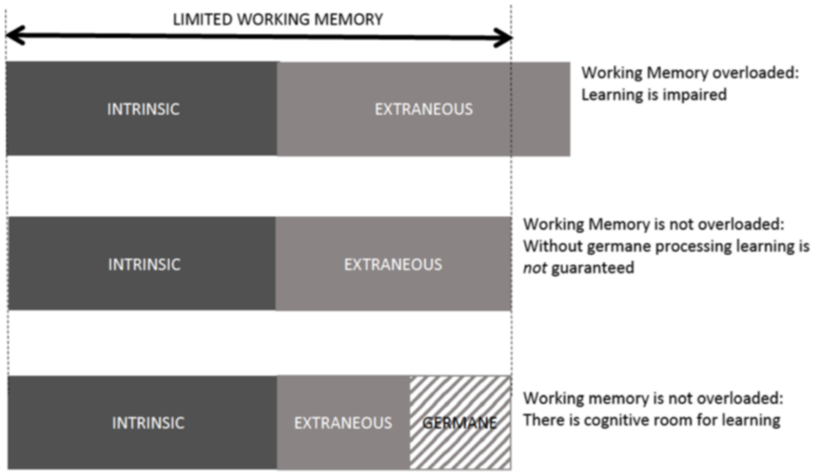


Figure 2.1: Effects of working memory limitations (Fraser et al., 2018)

When the working memory is exposed to too much information to process and thereby exceeds its capacity, a so-called *cognitive overload* occurs (Mayer and Moreno, 2003). This overload may occur when the sum of the intrinsic and extraneous load is too high, since they are additive (Paas et al., 2004). Within the total composition of these three components, it is desirable that there is always room for germane load to guarantee the learning process (Fraser et al., 2018).

The extraneous load is especially the important factor in this case since there are many ways to influence this factor via, for example, *usability.* Elements such as irrelevant graphics or illogical layouts can contribute to higher extraneous load. In this research, (background) music is the extraneous load in question. Music (and sound in general) as an external source is, contrary to design features, a factor which cannot always be minimized, avoided or designed for. The extraneous presence of music may either be put on deliberately, like within our modern 'streaming everyday life' (Hagen, 2016), but can also occur without actively choosing for it (e.g., music in public transport while reading or writing). But other more general sound-related sources, such as conversations of people next to you, are too of quite an importance since they could interfere with our cognitive capacities.

The significance of avoiding cognitive overload was shown by Albers (2011) who stated four potential consequences after researching the influence of increased extraneous load in web design. Not only may it result in (1) a noteworthy increase of mistakes being made during the digital tasks, but it can also even (2) force a full stop of the task(s) instead of trying to continue keeping all the balls in the air at once. The (3) ensuing caused frustration demotivates even to search for adequate solutions among the users. Lastly, (4) information appeared to be misjudged or taken for granted without strong evaluation. The question is whether Albers' arguments still hold for background music during digital tasks instead of web design issues.

Measurements of cognitive load

Research has experienced some methods to measure our cognitive load, such as respiratory changes (Grassmann et al., 2016), eye tracking (Zagermann et al., 2016), and surveys as the NASA-TLX (Hart, 2006) or the *Mental Effort Scale* (Paas, 1992). However, the former is limited to the extent that only a few variables can be used to draw conclusion and it has barely been tested in the context of HCI. The latter tends to be accurate but remains a subjective solution. Surveys, moreover, are sometimes inaccurate and unreliable and participants not always tell the truth. Biases like social desirability or acquiescence often tend to bend to results of these questionnaires (Bogner and Landrock, 2016). However, using surveys as an additional measurements could be useful for comparing and interpreting them with objective results. Although cognitive load is a complex matter and has its specific way of measurement needed in a wide spread of different contexts and sciences, eye tracking stands out in HCI as one of the most widely used methods on cognitive load (King et al., 2019; Zagermann et al., 2016). Eye tracking has an objective character and many variables to use during analysis. Those variables and usage will be explained in a later section.

2.2 Background music: motivator or disturber?

Background music has been widely studied as one of the most predominant independent variables in all kinds of fields of science, ranging from learning and gaming to sports and relaxation. In this paragraph, background music will be discussed in two different sections, covering both its motivational appeal and its cognitive impact as a factor of extraneous load.

2.2.1 Motivational character

In science, the *Self-Determination Theory* by Ryan and Deci (2017) is a fundamental base of our knowledge about motivation. Motivation, here, is discussed as a twofold of extrinsic motivation and intrinsic motivation. Where the former motivates people to act by external rewards such as money, the latter is about our stronger internal sources as a need to gain knowledge or independence (Ryan and Deci, 2017). When individuals do somethings because they find it inherently enjoyable or interesting, it is called intrinsic motivation (Linek et al., 2011). This type of motivation sometimes tends to be somewhat stronger and more sustainable than extrinsic motivation leading to better outcomes in learning and performance. However, extrinsic motivation is equally useful and important due to its potential to raise motivation for tasks people might not find immediately rewarding or enjoyable. In these kinds of situations extrinsic motivators initiate engagement and increase the chance to a successful start of an unappealing task.

In the context of this *Self-Determination Theory*, background music can be seen as a positive contributor to extrinsic motivation since it is added to the situation rather than caused from within the individual him or herself. It is likely to make a task more interesting or enjoyable, can influence a person's mood, concentration level, and even overall performance. Indirectly, background music can even support intrinsic motivation as tasks become more interesting and therefore enhancing the motivation to continue with the task. According to Shuler (1991), it can even be added that background music can act as both a stimulus and reward for learning. Moreover, in field studies where students were exposed to background music, often positive notes were made. Students tend to be more relaxed (McGovern, 2000) and felt better while soft music was playing in the background (Dinsmore, 2003). Similar findings appear in studies concerning sports and exercising. Musical accompaniment seems not only to result in increased work output, but also to reduce the rate of perceived physical exertion, due to synchronization of tempo (Karageorghis and Terry, 1997). This effect suggest that the tempo and pace of the simultaneous activity is likely to adjust to the tempo of the music being stimulated. Kallinen (2002) has also found this phenomenon in other disciplines besides exercising, namely reading.

Returning to the context of HCI, music and its tempo have significant influence in gaming context too. Tempo is to affect player immersion (Rogers et al., 2019) making the player feel more engaged with the gaming experience. But tempo also has potential to affect psychological stress and alertness (Hébert et al., 2005) positively while playing digital (educational) games. Concluding, based on a review of related literature (Karageorghis and Terry, 1997), selected music can improve both enjoyment and adherence. Therefore, from these different types of disciplines, it can be concluded that tempo is a predominant factor in music with potential to affect our motivation and to correlate with pace in other activities. Thus, tempo will be included in this research.

2.2.2 Cognitive impact

As discussed in earlier sections, background music can be seen as a form of extraneous load. This source of information is stimuli to process for our brain, while not being particularly relevant or needed for the task itself. In line with the theory of *Cognitive Load* (Sweller et al., 1998), background music takes up cognitive capacity and thereby limits our working memory. Therefore, one could assume that background music has detrimental effects on our cognitive abilities. However, some studies argue the contrary. The so-called *Mozart Effect*, stating that people enjoy a brief improvement in visual-spatial reasoning after listing to Mozart, has caused quite the hysteria in both science and society. For a time, it was thought that the exposure of Mozart' music improved long-term IQ - although there were quite a few comments regarding whether it was classical music that did the job (i.e., if other genres would have had the same results). After all, multiple reviews have shown that these positive effects were actually very small, if there were any differences at all. Most repeated experiments showed inconsistencies and did not find significant results (Jenkins, 2001). Modern literature mostly tells us that the effects of background music during (digital) tasks is mostly inconsistent due to the great scale of possible context. The tasks themselves, the subject's surroundings, and the characteristics of the music all have yet unpredictable roles for the effects on our cognitive capabilities.

Besides the tempo as discussed earlier, the presence or absence of lyrics are too of great influence on the cognitive process of background music. In contrary of tempo synchronization effect, music with lyrics have potential to clash with the subject's flow and attention performance (Shih et al., 2012). In an independent A/B experiment, Shih et al. (2012) found that the negative effect on attention was larger for music with lyrics than music without lyrics. They continued to relate their findings to a theory of Russell and Snodgrass (1987). This theory suggests that the complexity of environment stimuli is responsible for a certain amount of human arousal and attention, and thus that the higher the complexity, the larger the effect on human. Shih et al. (2012) firmly connect their findings to this theory (saying that music with lyrics have higher complexity and thus are more detrimental), even though Russell and Snodgrass are particularly focused on a scope concerning visual complexity of physical spaces (e.g., architecture), and do not mention any connection with music.

However, the solely findings of Shih et al. (2012) are backed up within science. Souza and Barbosa (2023) also found enough evidence to state that music with lyrics disturbed verbal memory and reading memory, whereas instrumental music did not. Participants seemed to be aware of this detrimental effect. Therefore, it can still be carefully stated that music with lyrics have a more detrimental effect on our cognition than music without lyrics.

Measurements of background music effects

From both the paragraph on motivational character as cognitive impact, it can be concluded that tempo and the presence or absence of lyrics have their effects on our human abilities such as reading performance, pace, and attention. In the previous section on cognitive load, eye tracking has been proposed as a suitable and objective method in HCI for cognitive load. Concerning background music, eye tracking stays an appropriate method since it allows variables as reading performance, pace, and attention to be measured. This method allows for a wide range of variables to be used. In the next section, the functioning of our eye and therefore the method of eye tracking will be elaborated.

2.3 Visual Attention

The functioning of the human eye can roughly be broken down into two forms of vision; (1) the *central vision* is the area one is focusing on and (2) the *peripheral vision* represents the rest of the regions of the scene outside the point of fixation. Because of the way our retina is designed, elements in central vision are caught by the *fovea*, a small pit where visual resolution is much higher than in the outer retina (Wells-Gray et al., 2016). Therefore, a human tendency arises to direct our centre of gaze towards the most relevant areas of the view (Le Callet and Niebur, 2013).

During stimulation, the eyes make constant movements and centre on certain points with the central vision (i.e. fixations) resulting in a *scan path*. Altogether these movements are known by the name *overt attention*. Where overt attention represents the gazes visible for external observers, its antonym is *covert attention*. Covert attention, in turn, describes the unconscious attention where no physical eye movements are detected and thus the eyeball ought to be stationary (Goldstein and Van Hooff, 2018). Although the eye is not in movement, covert attention has a very solid contribution to the human attention. Research by Perkovic et al. (2023) states that the covert attention is accurate in decision-making as it simultaneously registers information and impulses outside the focus. Former research already confirmed its importance in tasks such as reading (Inhoff et al., 1989) and its acceleration of pace in general information processing (Carrasco and McElree, 2001). Multiple paradigms have been experimented on to determine the workings of covert focus, such as the *Posner Spatial Cueing Task* (Van Der Stigchel and Theeuwes, 2007) or an introspective access to shifts of attention (Reyes and Sackur, 2017) but those tend to be found less convenient and less secure to draw conclusions compared to direct overt measurements. However, in many of these research covert and overt focus have also been proved to be correlated; *micro saccades* (i.e., small, and precise overt actions) tend to speak for shifts in covert attention (Hafed and Clark, 2002; Shepherd et al., 1986). Understanding this interplay between overt and covert attention aids in creating interfaces that fits in with users' subconscious information processing (Goldberg and Kotval, 1999).

But, due to this more direct measurement character of overt focus and the discovery that covert attention is a derivative of micro-overt attention, overt measurements are being held as a more useful method in this field of science (Le Callet and Niebur, 2013). In the next section, there will be elaborated on the method that can capture this overt attention and how it can be used for research.

2.4 The method of Eye Tracking

Analysing gaze patterns provides insights into what elements attract overt attention and how users navigate through content. Eye tracking studies can unveil how users distribute their central and peripheral vision during interactions and have shown their appliance in all kinds of fields such as UI-design and e-commerce (Dospinescu and Percă-Robu, 2017) or gaming (Soler-Domínguez et al., 2017).

In research, the methods of direct overt measurements have quickly evolved due to technological improvements. The first eye tracking system, built by Edmund Huey in 1908, was a machine attached to a lens with a small opening for the pupil of the participant. Where older eye tracking methods like the latter were intrusive, less accurate and unable to distinguish eye movements from head tilts (Research, 2014), modern methods offer not only an objective assessment of each component of the eye, but also facilitate variables like exposure time, blinking rate, velocity, pupil dilation, scan paths, saccades, and most importantly cognitive load (King et al., 2019; Zagermann et al., 2016). The proven underpinning that eye tracking suits for objective overt analysis and as a stable indirect measurement for cognitive load, makes it a firm method for this research subject. In this section, an enumeration of relevant overt measurement variables of modern eye tracking will be introduced:

2.4.1 Fixations

In the field of science, a *fixation* is described as a brief pause during visual contact where people keep their gaze stationary for a relatively longer period of time. This voluntary movement lasts about 200-400ms (Salvucci and Goldberg, 2000), and its target is called the area of interest (AOI). A point of fixation can be an indicator for the difficulty of processing information relevant for the user. The duration of fixations and their rates are useful variables for assessing the cognitive resources occupied by a certain task. For both the former and the latter, it was found that they indicate the difficulty in extracting information (Wang et al., 2014), or the degree of engagement of an object (Just and Carpenter, 1976). Wang et al. researched the fixation duration and fixation rate in the context of visual website complexity during simple tasks. Their results indicated that the fixation rate increased with higher visually complex websites, but for the fixation duration no significant differences were found between low and high complexity. However, when the individuals were exposed to more complex tasks, the fixation duration did follow the same increase as fixation rate.

Surprisingly, other research proposes that fixation duration and rate may behave otherwise. Zagermann et al. (2016) states that fixation duration and rate are indicators of an increment in attention and therefore expects the following: the higher the cognitive effort, the longer the fixation duration and the lower the fixation rate. From this current knowledge of fixation duration and rate during cognitive challenges, it may be stated that a disagreement exists on their behaviour which will be taken into account for the hypothesis of this research.

2.4.2 Saccades

A saccade is the follow-up of fixations. It indicates a rapid path of eye movements between the fixations, visualized in Figure 2.2 below. It is described as the fastest movement the body can produce ranging from 30 to 80 milliseconds (Zagermann et al., 2016). Scan paths are known as popular visualizations, showing the velocity and length of each saccade. The velocity of saccades is shown to increase with higher cognitive efforts and to decrease when becoming tired (Fritz et al., 1992). With that, saccades are a potential variable to use when researching changes in cognitive activities.

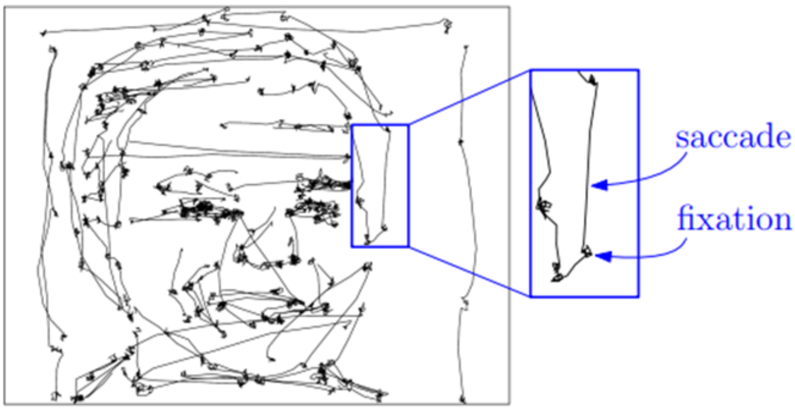


Figure 2.2: Example of fixation and saccade in eye tracking (Scalera et al., 2021)

2.4.3 Pupil Dilation

In contrary to fixations and saccades, pupil dilation is an involuntary reflex. Depending on the stimulus, the human pupil can narrow and widen to respectively 1.5mm and 8mm (Zagermann et al., 2016). This physiological response of the pupil is positively associated with the difficulty of the task and so the cognitive effort to solve it Chen et al. (2011), as that when the required effort increases, the pupil size increases too. It has also been found that pupils decrease in size towards the end of a task, suggesting that a decrease relates to tiredness (Porta et al., 2012).

When researching pupil dilation, one must be careful concerning environmental control. Pupils tend to dilate in darkness to catch more light, and contract in brightness to tame the overexposure of light. Therefore, a controlled environment must be secured before experimenting with pupil dilation.

2.4.4 Blinking

Blinking rate is a widely used variable in eye tracking. This both voluntary and involuntary response is associated with cognitive load in a way that a lower rate suggests high mental effort (Chen et al., 2011). The speed at which we blink (i.e. the movement of our eyelid), known as blinking velocity, tends to be aligned with an increase of fatigue (Sharma and Dubey, 2014).

2.4.5 Heatmaps

The aggregation of the above (fixations and saccades) allows to recreate this solely data into a "distribution of visual attention" (Punde et al., 2017). Heatmaps are colour-based pictures of a certain view where often red and green areas represent areas with a respectively high and low level of interest, as shown in Figure 2.3. Heatmaps are often visualizations of the combination of data from multiple participants.

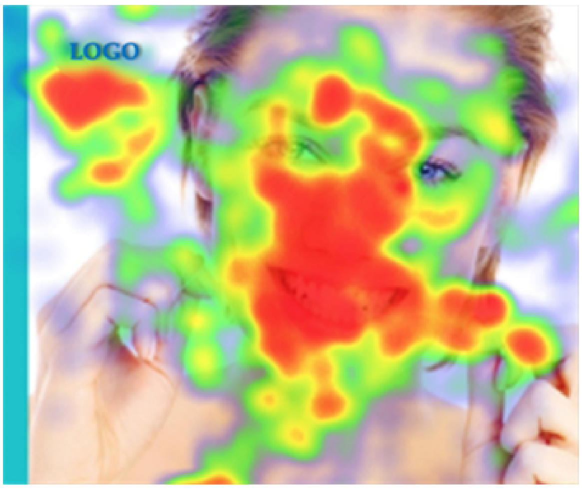


Figure 2.3: Example of Heatmaps in eye tracking (Nichifor et al., 2021)

Chapter 3

Research Questions and Hypotheses

3.1 Research Questions

After the elaboration on the literature of involved subjects, the next step is to formulate logical research questions that can be deduced from the literature to the context of this paper. The questions are formulated below starting with the main research question and followed by sub questions, supported with a conceptual model (Figure 3.1).

> ***What effect does the presence and tempo of background music have on our cognitive load during digital tasks when measured with eye tracking?***

- *Does the presence of background music provoke significant changes in fixation duration, fixation rate and pupil dilation during digital tasks?*
- *What effect does the tempo of background music have during digital tasks on fixation duration, fixation rate, and pupil dilation?*
- *Can eye tracking be reliably used to measure the effects of background music on cognitive load during digital tasks?*

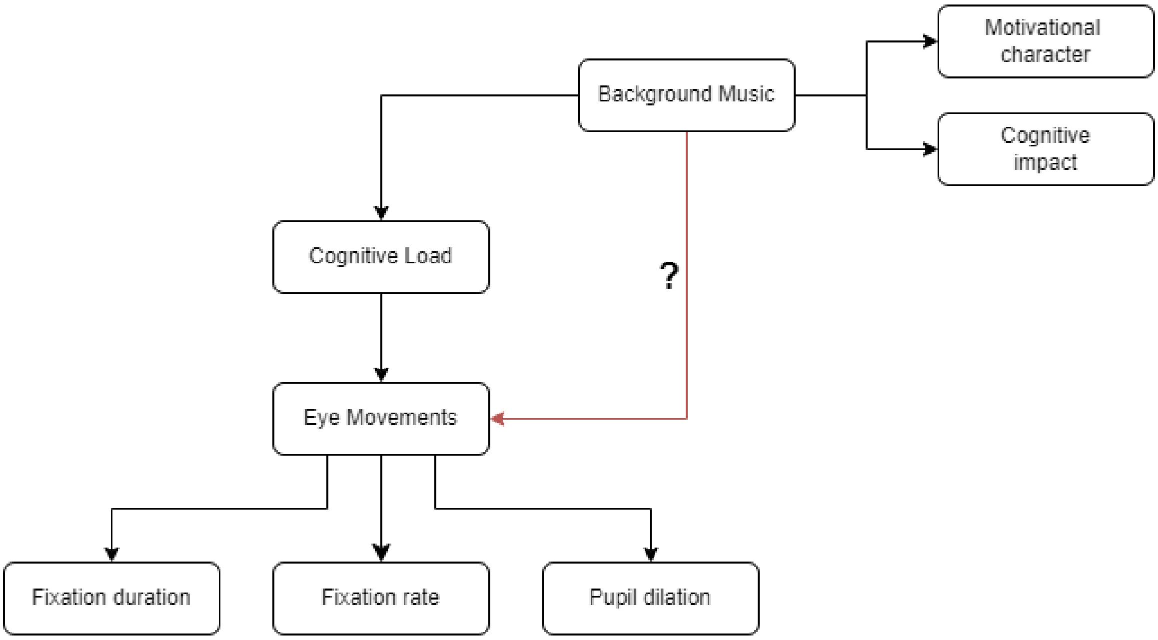


Figure 3.1: Conceptual Model

3.2 Hypotheses

After the elaboration on the literature of involved subjects, the next step is to formulate logical and measurable hypotheses that can be deduced from literature to the context of this paper.

Reflecting on the theory, background music is generally stimulated as content that is not directly relevant to the task and thus increasing the extraneous load (Merriënboer and Ayres, 2005). Thus, background music reserves parts of our cognitive capacity according to the *Cognitive Load Theory* by Sweller et al. (1998). This given, leads us to the first key principle that background music, as extraneous load, increases the load in human cognition.

Our second key principle arises from the objective measurement eye tracking for cognitive load (Zagermann et al., 2016). Research has shown multiple effects of either fixation duration, fixation rate, and pupil size with each multiple explanations. On the one hand, Zagermann et al. (2016) has proposed that "the higher the cognitive effort, the longer the fixation duration and the lower the fixation rate". However, his colleagues in this field of science have proven otherwise, stating that fixation rate will increase along with an increase in cognitive load (Wang et al., 2014). Additionally, the pace of our saccades increases when higher cognitive efforts are being made (Fritz et al., 1992). Concerning the pupil size, research shows that it is positively related to the level of difficulty and the cognitive effort required for a task (Chen et al., 2011), but it remains highly dependent on the kinds of task and environmental factors. Concluding, from this second key principles it can be suggested that background music has yet an unclear effect on fixation duration, fixation rate and pupil size.

The third key principle taken into consideration for the hypotheses proposals is that the theory has also shown that, according to the *Self-Determination Theory* (Ryan and Deci, 2017), background music can be seen as a contributor to extrinsic motivation because of its positive effect on the level of interest and joy during a task – and thus decreasing the cognitive load. Together with the synchronization effect of background music tempo on the tempo of the activity in sports (Karageorghis and Terry, 1997), gaming (Hébert et al., 2005) and reading (Kallinen, 2002) – this third key principle indicates the expected motivational effects of background music which in turn have their potential to influence the cognitive load. However, it remains unclear whether those effects are either positive or negative, due to the wide range of background music characteristics and different kinds of tasks possible.

Due to the entanglement of these three key principles above, three non-directional hypotheses will be proposed below. Instead of predicting a specific direction, these two-tailed hypothesis empowers exploratory science.

> *H1: The presence and tempo of background music during digital tasks will have an effect on fixation duration, where fast tempo background music will have a greater effect than low tempo background music.*
>
> *H2: The presence and tempo of background music during digital tasks will have an effect on fixation rate, where fast tempo background music will have a greater effect than low tempo background music.*
>
> *H3: The presence and tempo of background music during digital tasks will have an effect on pupil size, where fast tempo background music will have a greater effect than low tempo background music.*

With background music as an extraneous load, less cognitive capacity is expected to be available to commit to a digital task. Therefore, it is believed that listening to background music slows the user down and thus results in a longer time spent in the task (*H4*).

> *H4: The presence and tempo of background music during digital tasks will have an effect on the time spent, where fast tempo background music will have a greater effect than low tempo background music.*

Chapter 4

Methodology

4.1 Experimental Design

In order to (dis)prove the hypotheses, an eye tracking experiment has been performed in a controlled environment. This between-subjects experiment had two experimental conditions and one control group. In the experimental conditions, the independent variable background music consisted of either (1) fast tempo or (2) slow tempo instrumental songs, while the control group had (3) no background music. Cognitive load - measured with eye tracking through fixation rate, fixation duration and pupil dilation – acted as dependent variable (see Table 4.1).

During the experiment each participant had to execute two digital tasks on a desktop computer. Both the condition of background music as well as the sequence of these tasks were equally random assigned for each participant. The content of the background music and tasks will be explained in the following paragraphs.

The choice for a between-subjects design is based on its advantages such as avoiding carryover effects like becoming more skilful in the task and fatigue, but also less testing time per participant.

Table 4.1: Experimental Design

Background Music	Task 1	Task 2
No Music (control)	Gaming	Reading
Slow Tempo	Gaming	Reading
Fast Tempo	Gaming	Reading

Note: Task Sequence is random.

4.2 Dependent Variables

The effects of background music will be measured with a few eye tracking variables. As proposed by Zagermann et al. (2016), eye tracking can be used as a reliable measurement for cognitive load using multiple variables. The *iMotions10* software - to which the *Smart Eye AI-X* eye tracker is connected - offers the measuring of many variables, including the variables needed to test this study's hypotheses. Variables needed for the hypothesis testing are enumerated and collaborated on below.

1. **Fixation duration**. Measuring the effect of the independent variable for *H1* requires the fixation duration. Throughout the task the eye tracker will capture each fixation with its coordinates and the duration in milliseconds. Often, the duration of a fixation ranges from 200 to 400 milliseconds (Salvucci and Goldberg, 2000). A jump from fixation to fixation can be determined by looking at the gaze coordination. When the gaze coordination differs significantly, it can be noted as a new fixation (i.e., this change of coordinates should happen after 200-400ms). Figure 4.1 shows the jump in coordinates as an example.

2. **Fixation rate**. In preparation of *H2*, another dependent variable from the eye tracker must be gathered, the fixation rate. This eye tracker output variable is measured a derivative of the fixation duration. The amount of significant gaze changes can be added as a count of fixation. The *iMotions10* software package offers an automatic fixation rate index in the output file of each participant.

3. **Pupil Size**. The pupil dilation will be measured in millimetres. The output data deliver both the pupil size of the left and right eye. This variable will focus on the change of size during the task (increase or decrease) to answer *H3*.

4. **Time Spent**. For *H4*, the time needed to complete the experiment. Since the gaming task has a fixed duration (i.e. each participant plays exactly 4 minutes),

only the time spent on the reading task had to be calculated since the gaming task had a fixed duration. The eye tracking device automatically starts a timer for the complete experiment. This is measured in milliseconds but transformed to seconds and split for each task as described in section 4.6 'Data Handling and Preparation'.

Row	Timestamp (ms)	GazeLeftx	GazeLefty	GazeRightx	GazeRighty
17	295.9464	1034	314	1074	316
18	312.5752	1037	308	1075	311
19	329.324	1045	297	1076	299
20	345.9608	1043	310	1071	312
21	362.6136	958	378	989	382
22	379.3544	940	450	985	454
23	395.956	939	459	977	463
24	424.7464	943	469	979	472

Figure 4.1: Fixation to fixation (around 200 to 400 milliseconds)

The enumeration above offers an objective method to measure cognitive load with eye tracking, but more methods have been implemented to add subjective measurements, control variables and demographics to the experiment. The subjective self-report measurements are added to compare and relate them to the objective measurements on cognitive load. The following two subjective scales have been presented to the participants:

1. **Perceived mental effort**. Cognitive load, often used interchangeably with mental effort, was measured with the *Mental Effort Scale* by Paas (1992). This subjective rating scale has been discussed as reliable and valid in literature (Hogg, 2007) and asks subjects to report the amount of mental effort that one has invested during a certain task or activity. This nine-point symmetrical category scale ranges from "very, very low mental effort" to "very, very high mental effort".

2. **Perceived level of difficulty**. As a second variant on the perceived cognitive load, participants were asked to report the level of perceived difficulty of the task. The *Single Ease Question* (*SEQ*) was used with a seven-step Likert scale ranging from "very easy" to "very difficult".

Several background variables have been asked to increase the internal validity of this research. This allows for more confidence in potential correlations and or causal relation between relevant variables. Participants reported: (1) age, (2) gender, (3) whether English is their native language, (4) highest achieved or current level of education, and (5) any reading disabilities such as dyslexia. After the reading tasks two quality control questions were asked such as "Which non-profit organisation was mentioned in the article?".

Lastly, a few control variables were asked on a five-point Likert scale from "Strongly disagree" to "Strongly agree":

1. "I am skilled in using computers."
2. "I am skilled in playing video games."
3. "I often listen to music during tasks where concentration is needed (e.g., solving hard puzzles/math/reflective thinking)."
4. "I often listen to music during tasks where concentration is NOT needed (e.g., vacuum cleaning or drawing)."
5. "I prefer working and/or studying with music on."

4.3 Participants

During a period from April 15th to May 13th of 2024, participants have been recruited using researcher' social networks. Channels such as Instagram and Microsoft teams have been used for *snowball* and *convenience sampling* focusing on contacts from within and outside Utrecht University. A selected pool of participants, ranging from the age of 18-28 was preferred due to a similar experience in digital tasks because of their generational skills and upbringing with (internet) technology. For instance, eye tracking research in the past has shown that different generations had different viewing behaviour (Djamasbi et al., 2011). Besides, the limited range of age throughout all participants, offers a more reliable and firmer base to interpret the results, than when a broader range of age is used.

A total of 23 participated executed the experiment where males were most present with 73.9% compared to females with 26.1%. The participants ranged in age from 22 to 55 (M = 26.70, SD = 6.41), with 25 as the most common age. Although the control group (*M* = 29.57, *SD* = 11.37) had a higher mean and standard deviation than the fast tempo group (*M* = 25.63, *SD* = 1.41) and the slow tempo group (*M* = 25.25, *SD* = 2.05), no significant differences in age were observed across three conditions using an *ANOVA* ($F(2,20) = 1.023$; $p = .378$).

Most of the participants had a Dutch nationality (82.6%), while two participants were native English speakers, and others were Pakistani or Slovakian. Most participants were educated with either a master's degree (60.9%) or *highly professional education*/Dutch 'HBO' (21.7%) as most common. None of the participants indicated having any kind of reading disability such as dyslexia.

4.4 Materials

4.4.1 The background music

The single independent variable background music was realised in three conditions: (a) background music with a fast tempo, (b) background music with a slow tempo, and (c) no background music (control group). As mentioned in the subsection 4.4.4 'Setting', this background music is provided to the participants via a wireless noise-cancelling headset. Prior to selecting the definitive songs or musical compositions for implementation, a set of predetermined criteria was established. This has been done with the minimization of confounding variables in mind.

1. The background music should be of a genre and style that is likely to be listened to in a real life setting during digital tasks (e.g., pop music or hip-hop for students while reading study material).

2. The background music should not differ greatly in genre and style between the fast tempo condition and the slow tempo condition.

3. The background music should be clear from lyrics, avoiding the effects of potential sing along (out loud or in your head) behaviour.

4. The background music should be either known by all/most participants or by none.

5. The background music should maintain the same volume (in dB) during the whole experiment.

In line with these conditions above, systematic research has been conducted within the literature in this field of science (see Table A.1). From this exploratory research it has been concluded that most modern studies either used self-chosen music, pop, hip-hop, classical or a mixture of these genres as background music in context of driving performance, walking, learning, gaming, and reading digital news (Kallinen, 2002; Navarro et al., 2018; Rogers et al., 2019; Souza and Barbosa, 2023; Styns et al., 2007).

Table 4.2: Abridged Systematic Research: Background Music

Context	Author(s)	Year	Music	Slow*	Fast*
Reading digital news	Kallinen	2002	Bach's Brandenburg Concerto	66	92
Walking synchronization	Styns et al.	2007	Rhythmic instrumentals	50	190
Driving performance	Navarro et al.	2018	Preferred music	-30%	N/A
Gaming experience	Rogers et al.	2019	'Baby' and 'Fresh Fallen Snow'	80	120
Learning	Souza and Barbosa	2023	Lo-fi or Hip-hop	N/A	N/A

*Note: (1) This is an abridged version, full table in Appendix A. (2) * = Beats Per Minute*

As a result of combing the knowledge taken from the literature and the pre-formulated conditions, for this experiment, a mixture of soft-rock and pop music was chosen as background music in both experimental conditions (fast tempo and slow tempo; see Table 4.3). The selection of semi-known pop-songs were transformed into non-lyrical version using the AI-tool *Voice.ai* when an instrumental version was not directly available. Participants in both conditions were exposed to the music stimuli with sound levels ranging from 65 to 75 decibels (dB). In the control group without background music, participants still wore the wireless noise-cancelling headphones but were not stimulated with any sounds and/or music.

4.4.2 The reading Task

One of the two tasks that each participant has completed is a reading task. This type of task was chosen to represent a realistic digital task in real-life with less interactivity compared to the gaming task. While being exposed to background music the participant had to read a news article visualized in *iMotions*. The article "Boom

Table 4.3: Background Music Stimuli Songs

Condition	Title	Artist	BPM	Duration
Slow Tempo	Last Request	Paolo Nutini	81	03:49
Slow Tempo	Duo	Paolo Nutini	72	03:05
Slow Tempo	Karma Police	Radiohead	75	04:24
Slow Tempo	**Total Time**			**11:18**
Fast Tempo	Desperation	Paolo Nutini	169	03:35
Fast Tempo	Jigsaw Falling Into Place	Radiohead	166	04:09
Fast Tempo	The World Turned Upside Down	Coldplay	137	04:33
Fast Tempo	**Total Time**			**12:17**

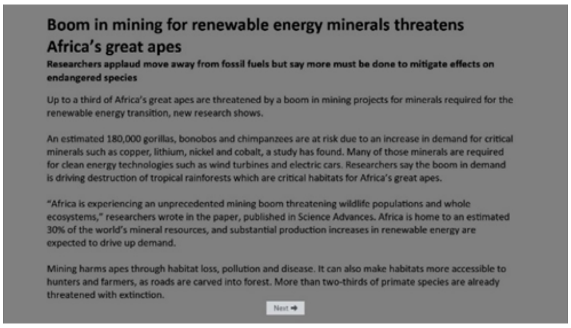
Note: BPM = Beats Per Minute

in mining for renewable energy minerals threatens Africa's great apes.", from The Guardian (Appendix C), was chosen due to its presumed target audience. The article is written at a level that is generally accessible to a broad audience, but it includes technical details and scientific terminology that might make it more challenging for younger readers. The style is mostly typical of the language used in mainstream journalism aimed at an educated public. This corresponded with the intended pool of participants for the experiment, college student and young adults. In the context of eye tracking experiment with reading tasks, the literature often uses similar stimuli from science news websites (Beymer et al., 2007; Josephson, 2008).

In terms of minimizing potential side-effects, the article was a secondary, less prominent article taken from a subcategory of on The Guardian's website. This prevented the possibility that participants had already read this article. The article was released a week before the start of the experiment and the average time spent on reading the article was 03:42 minutes.

Figure 4.2: Instructions prior to the reading task

Instructions were given before the news article was shown (see Figure 4.2). Participants were asked to NOT read out loud. When the reading task (see Figure 4.3a) was completed, two quality control questions were prompted to the participant to check whether the participant had fully and/or sufficiently read the article (see Figure 4.3b).



(a) First page of the reading task

(b) Two quality control questions

Figure 4.3: Reading task

4.4.3 The gaming task

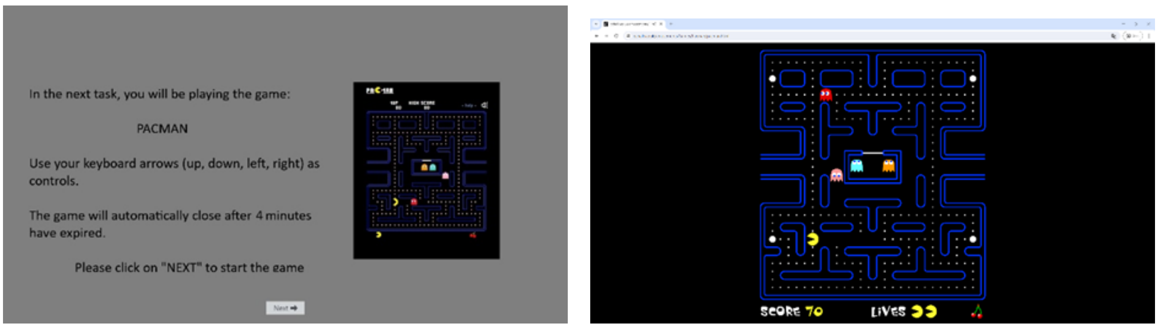
The second task represented a more interactive and relaxing task. Therefore, a browser version of PacMan was prompted to the participants and they were asked to play for four minutes. The eye tracking software *iMotions* automatically opened a PacMan version from *echalk.co.uk*. This website provided a neutral gaming environment without any advertisements, pop-ups, or interruptions. Concerning the scope of this research, predetermined criteria had been stated below before choosing Pac-Man. With these criteria in mind, short systematic research has been established.

1. The game should be a non-violent game, since violent games are likely to elicit more initial responses such as anger, fear, or arousal-related player emotions than non-violent games (Ravaja et al., 2004).
2. The game should be playable without its original sound effects, so that the background music is solely present.
3. The game should be easy to play for the first time, so that it does not require training or gaming skills.
4. The game should be controlled with a keyboard and/or mouse, avoiding skill-required controls such as joysticks.
5. The game should stimulate eye movement (e.g., scanning the environment to see where enemies are).
6. The game should be infinite in terms of playing time.

Table 4.4: Systematic Research: Gaming Task

Context	Author(s)	Year	Game	Notes
Cardiovascular responses	Baldaro et al.	2004	Puzzle Bobble (Taito 1995)	Non-violent
Physiological responses	Arriaga et al.	2006	Tetris Classic 1.0	Non-violent, non-action, single, no music.
Game strategies (eye tracking)	Alkan and Cagiltay	2007	Return of the Incredible Machine: Contraptions	Non-violent, decision-making and problem solving.
Dynamic game balancing	Tijs et al.	2008	PacMan	Avoiding undesired player emotions
Information Seeking	Józsa and Hámornik	2012	Museum of Thieves (Find the differences)	

Based on the predetermined criteria and the systematic research (see Table 4.4), PacMan was chosen as the selected gaming task. Namely, PacMan is easy to play for beginners as well as more advanced gamers. The instruction and controls are clear and simple, and the role of its sound effects is not crucial. The *echalk* version of PacMan (see Figure 4.4) provided an infinite playtime and offered a simple handling to 'Play Again' in case that the participant was shown 'Game Over' during the four minutes they had to undergo. The non-violent character of PacMan minimized the potential responses such as stress or fear.



(a) Instruction prior to the gaming task **(b) PacMan on echalk.co.uk**

Figure 4.4: Reading task

4.4.4 The setting

The experiment was conducted in a laboratory located in the *Human-Centred Computing Lab* at the University of Utrecht. Here, participants took place behind a 27-inch monitor with full HD resolution (1920 x 1080 pixels) connected to a desktop running on Windows 10. The *Smart Eye AI-X* eye tracking device was attached to the bottom frame of the monitor and ran on the software package *iMotions10*. The distance between the monitor and the participants was approximately 60 centimetres.

Participants controlled the computer with both a wired mouse and keyboard. The background music was be provided using a wireless noise-cancelling S*ony WH-1000XM3* headphone connected to an *Apple iPhone 13* using Bluetooth. This setup involved the *Wizard of Oz* method (Preece and Sharp, 2015) where participants ought to believe that the music was automatically turned on/off, while in reality the researcher operated the music. The setup is visualized in Figure 4.5.

This laboratory was free of other persons, machines, or devices with the potential to distract to participants with sound or lights, creating a silent non-distracting space. Due to the dependent variable concerning pupil dilation, all blinds were shut so that the natural lightning was consistent throughout all participants. With the solely use of the artificial lights, it was attempted to maintain a consistent pupil size baseline.

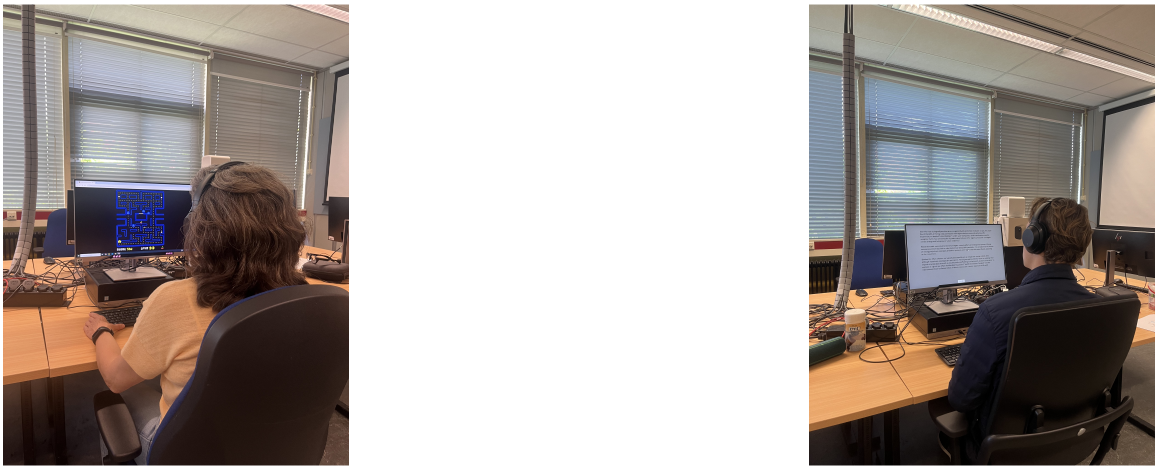


Figure 4.5: Experimental setting during the gaming task (left) and the reading task (right)

4.4.5 Other Materials

Online survey tool *Qualtrics* has been used twice. Before the experiment, participants had to sign an online consent form (Appendix D). After the experiment, participants had to fill in a short survey for the basic demographics and other control variables (Appendix E).

4.5 Procedure

In Figure 4.6, the flow of this experiment procedure can be found. Through an online invitation, participants were invited to participate in the research and were able to choose a preferred time slot in the experimenting period. A brief introduction to the research was included in the invitation, as well as its duration, location, and requirements.

On that certain date, the participant was welcomed in the *Human-Centred Computing Lab* by the researcher. Firstly, the participant was be informed about the full procedure of the experiment, the data handling, their privacy, and their rights (e.g., to opt out at any time).

Afterwards, the participant was asked to sit down behind the eye tracking device and computer. The researcher then then explained what was about to happen in terms of their exposure to the eye tracking device. The position and height of the participants were then be modified so that it was comfortable and that the eyes were detectable for the eye tracking device to start calibration.

After calibration, the experiment was ready to start beginning with an online consent form (Appendix D) using *Qualtrics* that each participant had to sign with their name, date, and digital signature. After the consent form, participants saw the instructions for the first task (either gaming or reading, randomly assigned) and had to execute this task. The task was followed by two subjective scales where participants rated their self-report perceived experiences. The second task was automatically prompted next, again followed by two subjective scales. When both tasks had been completed, the participant was lastly prompted one last survey (*Qualtrics*) with demographics and other relevant questions (Appendix E). After the experiment, the participant was handed a chocolate bar as compensation.

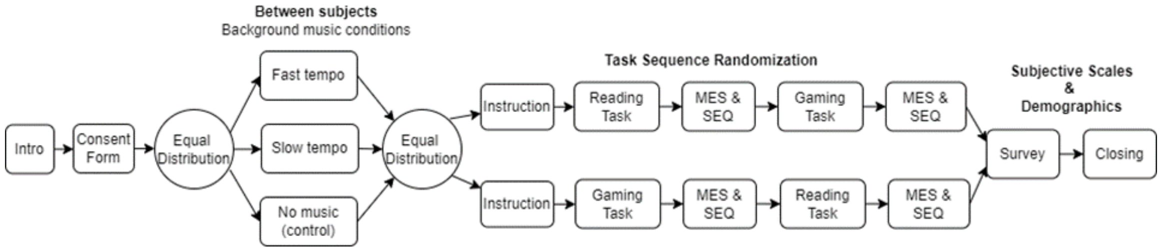


Figure 4.6: Procedure Flow

4.6 Data Handling and Preparation

The *iMotion10* eye tracking software package offers a wide range of variables and filters to be used. The standard filter offers timestamps, gaze coordinates, pupil size, and eye distance (to the tracker). However, an implemented add-on *R-analysed I-TV* filter allows for more in-depth research with variables such as interpolated gaze coordinates, gaze properties, fixation properties, and saccade properties.

Each participant is compressed into a resulting .csv-file of approximately 20.000 to 30.000 rows of data combining the standard filter variables and the *R-analysed I-TV* filter variables. To prepare and filter these data files, the IDE *Jupyter Notebook* running on *Python* (version 3.9) has been used. A script has been written that automates the process of cleaning and preparing all eye tracker data. This script also handles the data files containing the demographics as well as the responses on the subjective scales.

Below, a brief overview of the steps in this automated process (full script in Appendix B):

1. Data is being imported as .csv-file from *iMotions10* in the *Jupyter Notebook*.

2. Unnecessary rows and metadata are deleted/skipped.

3. Columns as "Background Music" and "Task Sequence" are added based on values within the file.

4. Dependent variables are calculated or transformed (e.g., taking the mean, counting the fixations).

5. *DataFrame* is formed where each row contains all relevant eye tracking variables for a participant.

6. Demographics from the survey and the answers from the subjective scales are merged on participant ID.
7. Final merged DataFrame is being exported to .csv-file for analysis in *IBM SPSS statistics 29*.

Chapter 5

Results

5.1 Exploratory analysis

To get an overview of all variables, an exploratory analysis has been performed in the form of a correlation matrix. The means, standard deviations and *Pearson*'s correlations of all dependent-, independent- and background variables can be found in Figure 5.1.

Concerning the mutual relations within the dependent variables, a significantly strong positive correlation was found between the fixation rate and the total time spent (r = .75, p < .01). Thus, as expected, the higher the fixation rate, the higher the total time spent and vice versa. Therefore, the dependent variable fixation rate has been transformed to a relative fixation rate per minute – which in turn had no correlation with the total time spent (r = -.16, p = .456). The relative fixation rate correlated moderately positive with the fixation duration (r = .52, p < .01). Furthermore, perceived *Mental Effort Scale* by Paas seemed to correlate with time (r = .50, p < .05), fixation duration (r = .53, p < .01) and lastly, the *Single Ease Question* (r = .74, p < .01).

As an exploratory analysis for the hypothesis testing, other moderately positive correlations were found for the independent variable background music with the dependent variables relative fixation rate (r = .58, p < .01), *Mental Effort Scale* (r = .53, p < .01), and the SEQ scale (r = .64, p < .01). This will be elaborated on in 5.2. So, the 'higher' the background music (control = 0, slow tempo = 1, fast tempo = 2), the higher the fixation rate, *Mental Effort Scale*, and the SEQ.

	n	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Condition[a]	23	1.96	.83	--																
2. Sequence[b]	23	1.52	.51	.16	--															
3. Total Time (sec)	23	503.09	57.77	-.21	.01	--														
4. Fixations (per min)	23	146.52	14.53	-.58**	-.09	-.16	--													
5. Duration (ms)	23	503.26	80.47	.10	-.48*	.32	-.52*	--												
6. Pupil Size (mm)	23	3.78	.33	-.15	-.3	.03	.23	.12	--											
7. Mental Effort[c]	23	4.91	1.32	-.53**	-.37	.50*	-.04	.53**	.36	--										
8. SEQ[d]	23	3.85	.92	-.64**	-.26	.26	.06	.26	.11	.74**	--									
9. Age	23	26.7	6.41	.25	.29	-.03	-.29	-.22	-.17	-.19	-.36	--								
10. Gender	23	1.26	.45	.40	-.03	-.06	-.15	-.02	.05	.00	-.06	.28	--							
11. Native Language	23	1.09	.29	.21	-.01	-.27	-.32	.36	.05	.20	-.03	.01	.17	--						
12. Education[e]	23	2.48	.90	-.28	-.07	-.30	.38	-.10	.08	.09	.28	-.26	-.10	-.17	--					
13. Computers[d]	23	4.13	.81	-.06	.05	.00	.35	.01	-.19	-.18	-.40	-.22	-.35	-.05	.28	--				
14. Videogames[d]	23	3.48	1.27	-.33	.09	.30	.33	.05	.06	.12	-.11	-.35	-.63**	.01	.11	.72**	--			
15. Concentration[d]	23	2.04	1.22	.05	-.18	.27	-.36	.23	-.24	.17	.05	.23	.06	-.01	-.23	-.10	-.16	--		
16. No Concentration[d]	23	4.26	.75	-.13	-.02	.27	.04	-.03	.32	.21	.16	.13	.06	-.32	.14	-.28	.05	.18	--	
17. Preference[d]	23	2.74	1.05	.09	-.07	.61**	-.24	.32	.00	.29	.14	-.08	-.04	-.22	-.15	-.01	.20	.64**	.49*	--

[a] 1 = Fast Tempo, 2 = Slow Tempo, and 3 = No Music (Control)
[b] 1 = Gaming, Reading and 2 = Reading, Gaming
[c] 9-point Likert scale
[d] 5-point Likert scale
[e] 1 = Higher Professional Education, 2 = Bachelor's degree, 3 = Master's degree, and 4 = Advanced Graduate or PhD
* $p < .05$. ** $p < .01$

Figure 5.1: Correlation Matrix

No significant relations have been found between the background variables age, gender, native language and education and the dependent variables using *Pearson*'s correlation and *one way ANOVA*'s.

Between the control statements (Likert scale behaviour-related questions), a few correlations were found between item 14 to 18 in Figure 5.1.

5.2 Hypotheses testing per task

The experiment consisted of two tasks, gaming and reading. To determine whether it was justified to regard and handle each dependent variable as a mean of the two tasks OR as two sole dependent variables per task, *paired samples t-tests* have been performed. For each dependent variable (fixation duration, fixation rate and pupil size), *paired samples t-tests* indicated significant differences between the two tasks as shown in Table 5.1. Therefore, the results for these tasks have been divided into two categories, so that each dependent variable has two sub variables. For example, the fixation duration has been calculated for the gaming task (first sub variable) and for the reading task (second sub variable). Thus, each hypothesis will be tested twice on both the sub variables for gaming and reading.

Table 5.1: *Paired Samples t-tests* between the tasks

Dependent variable	**mean: Gaming**	**mean: Reading**	**statistic**	***p***
Fixation Duration	644.26 (SD = 86.65)	362.70 (SD = 92.36)	$t(22) = 17.180$	$< .001$
Fixation Rate	131.13 (SD = 15.28)	192.87 (SD = 24.78)	$t(22) = -14.712$	$< .001$
Pupil Size	4.12 (SD = .47)	3.43 (SD = .24)	$t(22) = 10.033$	$< .001$

5.2.1 Background music and fixation duration

H1 predicted a direct effect of the presence and tempo of background music on the fixation duration. *The presence and tempo of background music during digital tasks will have an effect on fixation duration, where fast tempo background music will have a greater effect than low tempo background music.* This hypothesis was tested with a *one-way ANOVA* with background music (control vs slow tempo vs fast tempo) as independent variable and fixation duration as dependent variable (see Table 5.2).

Within the gaming task no significant difference in fixation duration had been found ($F(2{,}20) = .100$, $p = .905$) between the control group ($M = 653.57$, $SD = 61.85$), the slow tempo condition ($M = 633.25$, $SD = 85.15$), and the fast tempo condition ($M = 647.13$, $SD = 113.29$).

Within the reading task an adjusted *Welch ANOVA* was performed, due to inequality of variances, but no significant differences in fixation duration were found ($F(2{,}20) = .324$, $p = .731$) between the control group ($M = 387.71$, $SD = 110.92$), the slow tempo condition ($M = 351.75$, $SD = 30.84$), and the fast tempo condition ($M = 351.75$, $SD = 120.05$).

Due to the insignificant differences, ***H1* is to be rejected for both tasks.**

Table 5.2: Results Hypothesis 1: Fixation Duration

Dependent variable	Independent variable	test	statistic	*p*
Fix. Duration: Gaming	Background Music*	*One-way ANOVA*	$F(2{,}20) = .100$	.905
Fix. Duration: Reading	Background Music*	*Welch ANOVA*	$F(2{,}20) = .324$	.731

** = control group vs slow tempo vs fast tempo*

5.2.2 Background music and fixation rate

H2 predicted a direct effect of the presence and tempo of background music on the fixation rate. *The presence and tempo of background music during digital tasks will have an effect on fixation rate, where fast tempo background music will have a greater effect than low tempo background music.* This hypothesis was respectively tested with a *Kruskal-Wallis* test and a *one-way ANOVA* for the gaming and reading task with background music (control vs slow tempo vs fast tempo) as independent variable and fixation rate as dependent variable (see Table 5.3).

Within the gaming task a non-parametric *Kruskal-Wallis* test, due to non-normality of the variable, showed significant differences in fixation rate ($H(2) = 6.158$, $p = .046$) between the control group ($M = 125.71$, $SD = 10.21$) and the fast tempo condition ($M = 139.88$, $SD = 16.70$). The control group showed a significantly lower fixation rate during the gaming task than the fast tempo condition, using a *Mann-Whitney U* test ($U = -7.812$, $p = .021$).

Within the reading task, a *one-way ANOVA* showed significant differences in fixation rate too ($F(2{,}20) = 3.558$, $p = .048$), between the control group ($M = 178.29$, *SD* = 13.44) and the fast tempo condition (*M* = 208.63, *SD* = 33.05). A post-hoc-*Bonferroni* test indicated a significantly higher fixation rate for the fast tempo condition than the control group (*p* = .049, *mean difference* = 30.339).

Based upon these results, ***H2* is supported for both tasks.**

Table 5.3: Results Hypothesis 2: Fixation Rate

Dependent variable	**Independent variable**	**test**	**statistic**	***p***
Fix. Rate: Gaming	Background Music*	*Kruskal-Wallis*	$H(2) = 6.158$	.046
	Control - Fast Tempo	*Mann-Whitney U*	U = -7.812	.021
Fix. Rate: Reading	Background Music*	*One-way ANOVA*	$F(2,20) = 3.558$	.048
	Control - Fast Tempo	Post-hoc *Bonferroni*	mean difference = 30.339	.049

** = control group vs slow tempo vs fast tempo*

5.2.3 Background music and pupil size

H3 predicted a direct effect of the presence and tempo of background music on the pupil size. *The presence and tempo of background music during digital tasks will have an effect on pupil size, where fast tempo background music will have a greater effect than low tempo background music.* This hypothesis was tested with a *one-way ANOVA* with background music (control vs slow tempo vs fast tempo) as independent variable and pupil size as dependent variable (see Table 5.4).

Within the gaming task no significant difference in pupil size had been found ($F(2,20)$ = .456, *p* = .640) between the control group (*M* = 3.99, *SD* = .35), the slow tempo condition (*M* = 4.13, *SD* = .52), and the fast tempo condition (*M* = 4.23, *SD* = .53).

Within the reading no significant differences in pupil size were found ($F(2,20)$ = .058, *p* = .944) between the control group (*M* = 3.41, *SD* = .10), the slow tempo condition (*M* = 3.45, *SD* = .33), and the fast tempo condition (*M* = 3.42, *SD* = .25).

Due to the insignificant differences, ***H3* is to be rejected for both tasks.**

Table 5.4: **Results Hypothesis 3: Pupil Size**

Dependent variable	Independent variable	test	statistic	*p*
Pupil Size: Gaming	Background Music*	*One-way ANOVA*	$F(2,20) = .456$	.640
Pupil Size: Reading	Background Music*	*One-way ANOVA*	$F(2,20) = .058$	.944

** = control group vs slow tempo vs fast tempo*

5.2.4 Background music and time spent

H4 predicted a direct effect of the presence and tempo of background music on the time spent. *The presence and tempo of background music during digital tasks will have an effect on time spent, where fast tempo background music will have a greater effect than low tempo background music.* Due to unequal variances, this hypothesis was tested with a *Welch ANOVA* with background music (control vs slow tempo vs fast tempo) as independent variable and time spent on the reading task as dependent variable (see Table 5.5).

The analysis showed no significant differences in time spent ($F(2,11.64) = .646$; $p = .542$) between the control group ($M = 218.00$, $SD = 26.06$), the slow tempo condition ($M = 202.63$, $SD = 59.09$), and the fast tempo condition ($M = 244.13$, $SD = 81.34$).

Based upon these results, ***H4* is to be rejected for the reading task**.

Table 5.5: **Results Hypothesis 4: Time Spent**

Dependent variable	Independent variable	test	statistic	*p*
Time Spent: Reading	Background Music*	*Welch ANOVA*	$F(2,11.64) = .646$	.542
Time Spent: Gaming	*not applicable: fixed gaming time*	*of 4 minutes.*		

** = control group vs slow tempo vs fast tempo*

5.3 Additional analysis

5.3.1 Mental Effort (MES)

Concerning the subjective measurements, *one-way ANOVA*'s have been performed to analyse the *Mental Effort Scale* for the gaming and reading task with background music (control vs slow tempo vs fast tempo) as independent variable and perceived mental effort as dependent variable (see Table 5.6).

Within the gaming task, no significant differences in perceived mental effort were found ($F(2,20) = .324$, $p = .727$) between the control group ($M = 4.14$, $SD = 1.46$), the slow tempo condition ($M = 3.63$, $SD = 1.30$), and the fast tempo condition ($M = 4.13$, $SD = 1.56$).

Within the reading task, significant differences in perceived mental effort were found ($F(2,20) = 9.975$, $p < .001$) between the control group ($M = 4.14$, $SD = 1.68$), the slow tempo condition ($M = 5.75$, $SD = 1.28$), and the fast tempo condition ($M = 7.50$, $SD = 1.41$). A post-hoc-*Bonferroni* test showed a significant higher perceived mental effort score for the fast tempo condition than the control group ($p < .001$, *mean difference* = 3.357).

Table 5.6: Results *Mental Effort Scale*

Dependent variable	**Independent variable**	**test**	**statistic**	***p***
Mental Effort: Gaming	Background Music*	*One-way ANOVA*	$F(2,20) = .324$	.727
Mental Effort: Reading	Background Music*	*One-way ANOVA*	$F(2,20) = 9.975$	$< .001$

** = control group vs slow tempo vs fast tempo*

5.3.2 Level of difficulty (SEQ)

For the level of difficulty, a *one-way ANOVA* and *Kruskal-Wallis* test have been used respectively for the gaming and reading task with background music (control vs slow tempo vs fast tempo) as independent variable and perceived task difficulty (*SEQ*) as dependent variable (see Table 5.7).

Within the gaming task, no significant differences in *SEQ* were found ($F(2,20) = .515$, $p = .605$) between the control group ($M = 3.43$, $SD = 1.62$), the slow tempo condition ($M = 3.00$, $SD = 1.07$), and the fast tempo condition ($M = 3.63$, $SD = 1.06$).

Within the reading task, significant differences in *SEQ* were found ($H(2) = 11.782$, $p = .003$) between the control group ($M = 2.86$, $SD = 1.07$), the slow tempo condition ($M = 4.50$, $SD = .93$), and the fast tempo condition ($M = 5.50$, $SD = 1.20$). A post-hoc *Mann-Whitney U* test showed a significant higher perceived mental effort score for the fast ánd slow tempo condition compared to the control group (U = 3.500, p = .004; U = 6.000, p = .008).

Table 5.7: Results *Single Ease Question*

Dependent variable	Independent variable	test	statistic	p
SEQ: Gaming	Background Music*	*One-way ANOVA*	$F(2,20) = .515$	.605
SEQ: Reading	Background Music*	*Kurskal-Wallis*	$H(2) = 11.782$	.003
	Control - Slow Tempo	*Mann-Whitney U*	$U = 6.000$	.009
	Control - Fast Tempo	*Mann-Whitney U*	$U = 3.500$	.004

** = control group vs slow tempo vs fast tempo*

5.4 Overview

Below in Figure 5.2, an overview of the previous results can be found. For each dependent variable, the figure shows whether significant differences were found between the background music conditions. Green means significant differences were present, red means absent, and grey means that it was not applicable.

Figure 5.2: Overview of the results

Chapter 6

Discussion and Conclusion

This section will discuss the results from previous sections and combine these new insights with the existing literature and put them in perspective. Before diving into the interpretation of the hypotheses results, the reliability, validity, and the generalisability of the data will be evaluated.

6.1 Reliability, Validity, and Generalisability

This research intended to explore and broaden the knowledge about the connection between background music and our cognitive load using eye tracking, in addition to self-report measurement. The experiment including its questionnaires, consisting of a gaming task and a reading task, has been executed fully and successfully by all 23 participants. No participant was interrupted during the experiment or stopped on their own (e.g., asked questions or got stuck and needed help). There were no outliers found in terms of time spent as well as the eye tracking data itself. For the reading task, only one participant gave the wrong answer to one of the quality control questions. All other participants made no mistakes. To avoid a potential sequence effect of the tasks, the experiment's flow of each participant was randomly but equally assigned. Between these flows no differences were found in the data.

Before discussing the validity and generalisability, the interpretation of eye tracking data and results must be mentioned. Eye tracking is a method to capture eye movement via fixations, saccades, blinking and more. It shows us where we look at, when, and for how long – giving factual information about what and how a person is looking. However, no subjective interpretations of these action can be deducted.

Eye tracking exposes the objective actions of a person but does not show whether someone is actually paying attention or understands the content.

Concerning the validity, each individual participant underwent a short calibration of the eye tracking device to secure the correct capturing of their eye movements. The calibration sessions for all participants were rated by the eye-tracking device as either "good" or "excellent", except for one. This exception was caused by the participant's glasses. After consultation with the researcher, it was decided to proceed without glasses, as the participant claimed to have no major reading issues without glasses in this experimental setting. During analysis, data from this participant showed no significant differences from others in the same condition. The built-in eye tracking software also provided a quality score, rating the overall data quality and precision during the experiment on a scale from 0 to 100. For all participants, this score ranged between 86 and 100, with 97 as the average score ($SD = 3$). From this given, it can be concluded that the eye tracking data is valid.

Due to the representativeness and sample size, the generalisability must be interpreted with caution. The representativeness of this research mainly has areas of concern around the age, gender, and education. Namely, the mean age of this experiment was 26.7 years old, therefore under-representing older age groups. In gender a large proportion was male (73.9%) and around 80% of the participants were higher educated. Due to these representations, this research cannot just be extended to a whole population but indicates mostly young higher-educated Dutch men. Lastly, the sample size of 23 is sufficient for basic statistics and cautious conclusions but not strong enough for entire populations.

6.2 Interpretation results

The main research question of this project was '*What effect does the presence and tempo of background music have on our cognitive load when measured with eye tracking?*'. To answer this main question, the sub questions must be answered first – starting with the first sub question concerning the presence of background music.

> ***Does the presence of background music provoke significant changes in fixation duration, fixation rate and pupil dilation during digital tasks?***

When looking at the existing literature on the behaviour of these variables, it was expected that the presence of background music would make a significant difference compared to a control group without music. Background music itself could be characterized as an extraneous load within *Cognitive Load Theory* (Sweller et al., 1998) and therefore possibly overloading our cognitive resources during tasks that are perceived as difficult. Potentially, it could thus even limit the existence of germane load – meaning that there is no room for the process of learning and understanding the content deeply. Confirming this theory, the participants did indicate that they perceived a significantly higher mental effort while exposed to background music, but only for the reading task. Additionally, they added that the level of difficulty of the task increased when background music was present, but once again only for the reading task. Therefore, it can be concluded that in this research, background music can be characterized as significant extraneous load increasing the cognitive load for high-demanding attention tasks such as reading. The gaming task was less vulnerable to changes and thus one could argue that background music has less effect on perceived cognitive load during more low-demanding, relaxing tasks.

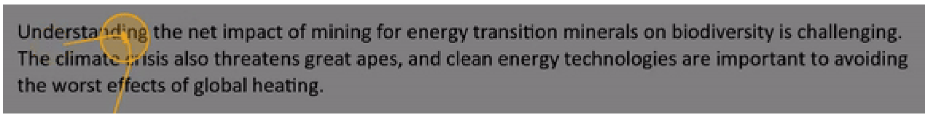
With this given, now the question raises whether the eye movements behave as expected when the cognitive load increases (i.e. significant differences in fixation duration, fixation rate, pupil size, and time spent between control group and background music conditions). However, in contrary to the hypotheses, no significant changes were found for the fixation duration, pupil size, and time spent. Therefore, this result is also not in line with earlier findings by Zagermann et al. (2016) who expected a longer fixation duration or Chen et al. (2011) who proved a positive relation between pupil size and level of difficulty and cognitive effort. An explanation for this dissimilarity could arrive from the earlier research on the motivational character of background music. According to the *Self-Determination Theory* (Ryan and Deci, 2017), music is ought to be a contributor to our extrinsic motivation due to its positive effect on the level of joy and interest during tasks. Besides, background music could have had a relaxing influence on the participants. From this point of view, one could argue that the background music might have decreased the cognitive load, and therefore counterbalancing the background music as extraneous load. But then again, participants did indicate an increase of perceived difficulty and thus not per se relaxing. Resuming, even though participants classified the tasks with background music as more cognitive challenging and difficult, their fixation duration, pupil size, and time spent did not act as expected from earlier research.

While no effect on fixation duration, pupil size, and time spent were found, results did show significant differences in fixation rate between the control group and the background music conditions. The fixation rate while exposed to background music was significantly higher for both gaming and reading compared to the control group. This is in line with earlier work from Wang et al. (2014) who argued that fixation rate would increase with cognitive load. Also differences between the slow tempo condition and fast tempo condition were found, leading us to the answer to second sub question.

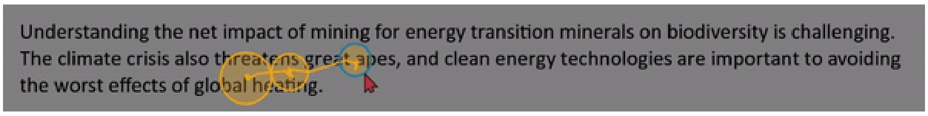
> ***What effect does the tempo of background music have during digital tasks on fixation duration, fixation rate, and pupil dilation?***

Quickly returning to the earlier variables: presence nor tempo did not affect fixation duration, pupil size, or time spent. But as mentioned above, background music did cause significant differences in the fixation rate during both the gaming and reading task. The fixation rate increased significantly from control group to the slow tempo condition and again from the slow tempo to the high tempo condition. The explanation for that these results align with earlier literature by Wang et al. (2014), might originate from the mentioned *Synchronization Effect*. Earlier experiment showed that the pace of an activity has the potential to synchronize with the tempo of the (background) music being stimulated, showed in multiple disciplines such as sports (Karageorghis and Terry, 1997), gaming (Hébert et al., 2005), and reading (Kallinen, 2002).

But besides this relatively harmless explanation for the increase of fixation rate, there might also be more detrimental effects. The fact that the rate increased together with the higher perceived cognitive load and level of difficulty, might have a negative effect on the efficiency and effectiveness of the task being executed. Where simple and relaxing tasks such as gaming are not easily endangered, the more attention-demanding reading task might be. If a cognitive overload was really the case during reading, it might be the case that information appeared to be misjudged or taken for granted without strong evaluation as explained by Albers (2011). During the reading task it even appeared that participants visibly were disrupted from their flow. Participants had to read words and parts of sentences multiple times before proceeding, indicating that they possibly did not fully focus or understood the content. An example of this phenomenon can be seen in Figure 6.1 where the upper bar illustrates a slow and steady reading process in the control group versus a fast and chaotic reading process in the fast tempo condition. The latter gets stuck on certain words and must read some parts multiple times. This disruptive flow phenomenon was also found by Shih et al. (2012) when experimenting with instrumental versus music with lyrics.



(a) Control Group



(b) Fast Tempo Condition

Figure 6.1: Visualised fixations and saccades.

Can eye tracking be reliably used to measure the effects of background music on cognitive load during digital tasks?

The eye tracking method in this research was valid and reliable. No precision errors were made and the continuity in the capturing of data made it a secure tool. But in order to decide whether it is a right tool to measure effects on background music on cognitive load, further arguments must be contemplated. As seen from the results on the perceived mental effort scale answered by the participants, it was clear that the tasks in the background music conditions were perceived as higher mental effort. Besides, the participants added that the level of difficulty rose when background music was present. One could therefore state that with background music the cognitive load was relatively high. But, except for the fixation rate, the same trend was not found in the eye tracking data. Fixation duration, pupil size, and time spent did not increase alongside with the perceived mental effort. Even though that earlier research by Zagermann et al. (2016) and Wang et al. (2014) both used eye tracking successfully for measuring cognitive load. Concluding, eye tracking can be used as a reliable measurement for cognitive load based on earlier work and some results of this experiment – however, in the context of additional background music, there is no clear evidence.

6.3 Limitations and future research

Firstly, the marginal availability of reliable and firm existing literature about background music and its effect on our eye behaviour minimized the power and confidence of the hypotheses made. Besides, the results of this research could only be put in perspective of - and backed up with - earlier research marginally. Therefore, no resolute conclusions could be made connection this research to earlier work.

A second marginal concern lies with the environmental setting of this research. Although the setting was kept natural as well as stable throughout all participants, the whole atmosphere and tone of the research might have influenced the results. Eye movement is normally an intuitive behaviour, but in alike research setting it could occur that participants behave differently knowing that their behaviour is being analysed. Besides, headphones were used to stimulate the music. For some participants it could be the case that they don't frequently use over-ear headphones, but rather use speakers or earbuds. Concerning this choice of freedom, the background music itself has some limitations. In reality, users often choose their own preferred music since streaming allows a wide-range of music to be played. However, due to practical limitation (experimental setting and unforeseen biases), this freedom of music choice could not be offered.

Furthermore, the division of the experiment in a gaming task and reading task has its advantages and disadvantages. As a positive aspect, it covered multiple grounds and a broader range of modern digital tasks. However, due to the limited research time, workforce and capabilities, each task could not be measured very long and thus limited eye tracking data for each participant was available. In future research it might be more effective and reliable to use single digital tasks and for a longer recording time. However, other tasks could also be considered since gaming and reading does not cover all regular digital tasks. Perhaps the effects of background music differs between gaming/reading and other tasks where something must be accomplished, such as problem solving or writing. When adapting this feedback in future research, one could also consider including measurements such as retention for more wide-range results of effects.

Lastly, due to the unclear evidence whether eye tracking is a reliable method in the context of the effects of background music on cognitive load, it is suggested that future research includes additional or substitutional eye tracking variables such as saccade (velocity) and blinking rate (and/or velocity). Besides, the strength and applicability of the results would benefit from including more scale question within the survey to enhance the subject insights from the participants.

6.4 Conclusion

The phenomenon of streaming allows us to listen to music everywhere and anytime. The rapid growth of streaming services to over a billion users worldwide, coupled with its accessibility via smartphones, wireless speakers, and laptops, means our (digital) tasks now have to share our cognitive load with music. During our daily tasks such as reading, writing, gaming, shopping and many more, music is now often added to the list of stimuli to process. The fun, relaxing and motivational character of music helps us during our daily lives but also has it impact on our attention, efficiency and productivity. This raised the question what the real effects of this musical exposure are.

After examining the quality of this research, its results, interpretations, and limitations guided by the sub research questions – the main research question can be answered.

> ***What effect does the presence and tempo of background music have on our cognitive load during digital tasks when measured with eye tracking?***

Background music during the digital tasks of gaming and reading seemed to increase the perceived mental effort and level of difficulty, and thus the cognitive load measuring with subjective scales. The high-demanding attention task, reading, seemed to be more vulnerable for changes than the low-demanding attention task, gaming. In context of our societal behaviour, music is more welcomed by people during easier tasks. This could be because music has the ability to elevate mood, reduce stress, and create a more pleasant atmosphere, which can make simpler tasks more enjoyable. On the other hand, during more complex or challenging tasks that require a higher level of concentration or cognitive effort, people may prefer silence or minimal distraction to maintain focus according to these results.

However, measuring this with the method of eye tracking, only the fixation rate increased. Within the results concerning fixation rate, also a significant role was found for the tempo of the background music. Fast tempo music seemed to amplify the effects compared to slow tempo music. For gaming tasks, this tempo synchronization effect can be interpreted as harmless. It could even have enhanced the excitement and immersion, making the gaming experience more engaging and enjoyable without significantly affecting our eye movements. But for reading tasks detrimental effects, such as lack of evaluation and disruption of flow, are realistic. The quick tempo was rather distracting, making it harder to focus on the text and perhaps to process the information effectively.

Similar significant differences were also expected to be found for fixation duration, pupil size, and time spent based on earlier but little research. In contrary, no evidence was found to conclude that these eye movements followed the same trend as the subjective perceived cognitive load.

Resuming, background music and its tempo seemed to increase the perceived cognitive load, but when measured with eye tracking no clear evidence was found to conclude that the presence and tempo of background music have a significant influence on our cognitive load during digital tasks.

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Appendix A

Figures and Tables

Table A.1: Full Systematic Research: Background Music

Context	Author(s)	Year	Music	Fast*	Slow*
Reading digital news	Kallinen	2002	Bach's Brandenburg Concerto	66	92
Emotional response	Webster and Weir	2005	unknown	72	144
Walking synchronization	Styns et al.	2007	Rhythmic instrumentals	50	190
Online shopping	Wu et al.	2008	unknown	72	92
Memory performance	Halpern and Müllensiefen	2008	Banjo music	N/A	N/A
Spatial and linguistic	Angel et al.	2010	Mozart's Sonata	N/A	N/A
Online shopping	Ding and Lin	2012	Iteyo and Allegretto	72	94
Reading comprehension	Thompson et al.	2012	Mozart's Sonata	110	150
Driving performance	Navarro et al.	2018	Preferred music	-30%	N/A
Gaming experience	Rogers et al.	2019	'Baby' and 'Fresh Fallen Snow'	80	120
Learning	Souza and Barbosa	2023	Lo-fi or Hip-hop	N/A	N/A

** BPM = Beats Per Minute*

Appendix B

Python Script

Underneath, the Jupyter Notebook containing the Python script for the data preparation can be found.

Eye Tracking Data Cleaning

Underneath a function is designed where each .csv-file (one per participant) from iMotions is processed. The following commands are executed:

1. Data is being imported as .csv.
2. Unnecessary columns are removed and some others are renamed clearly.
3. Participant ID, Condition and Flow (stimuli sequence) are retrieved from indicators within the .csv file (i.e., when the first value of column 'Stimuli' is 'Game', the flow is Game->Reading)
4. Split DataFrame: (1) Gaming and (2) Reading
5. Calculate total time spent, time spent per stimuli, amount of fixations and the mean fixation duration.
6. Save one row containing these variables, resulting in a DataFrame with for each particpant a row of the aforementioned variables.

```
import pandas as pd
import os

#Include
filenames = ['004_H1.csv', '003_L1.csv', '002_C1.csv', '001_H2.csv',
'004_L2.csv', '001_C2.csv', '003_H3.csv', '001_L3.csv', '002_C3.csv',
'002_H4.csv', '001_L4.csv', '001_C4.csv',
              '009_H5.csv', '008_L5.csv', '007_C5.csv', '006_H6.csv',
'004_L6.csv', '005_C6.csv', '003_H7.csv', '002_L7.csv', '001_C7.csv',
'001_H8.csv', '001_L8.csv']

#Predefine Dataframe before function will be running
eye = pd.DataFrame(columns=['ID', 'C', 'S', 'Total Time (sec)',
'Time_G (sec)' , 'Time_R (sec)', 'Fixations (abs)', 'Fixations_G
(abs)', 'Fixations_R (abs)',
                              'Fixations (min)', 'Fixations_G (min)',
'Fixations_R (min)', 'Duration (ms)', 'Duration_G (ms)',
                              'Duration_F (ms)', 'Pupil', 'Pupil_G',
'Pupil_R'])

def process_eye_file(filename):
    #Skip 26 rows of metadata
    path = filename
    df = pd.read_csv(path, skiprows=26)

    #Drop unnecessary columns
    drops = ['Row', 'EventSource', 'SlideEvent', 'StimType',
'Duration', 'CollectionPhase', 'EventSource.1', 'ET_GazeLeftx',
              'ET_GazeLefty', 'ET_GazeRightx', 'ET_GazeRighty',
```

```
'ET_TimeSignal', 'ET_DistanceLeft', 'ET_DistanceRight',
'ET_CameraLeftX',
             'ET_CameraLeftY', 'ET_CameraRightX', 'Interpolated Gaze
X', 'Interpolated Gaze Y', 'ET_CameraRightY',
             'Interpolated Distance', 'EventSource.2', 'Gaze X', 'Gaze
Y']
    df = df.drop(drops, axis=1)
    df.rename(columns={'SourceStimuliName': 'Stimuli'}, inplace=True)

    df = df.replace({'STIMULI - Game': 'Game', 'STIMULI 1 - Reading':
'Reading', 'STIMULI 2 - Reading': 'Reading', 'STIMULI 3 - Reading':
'Reading'})
    df = df.iloc[1:-2]

    # #Retrieve participant ID from filename and insert into DataFrame
    df['ID'] = os.path.basename(path)
    column_name = 'ID'
    df.insert(0, column_name, df.pop(column_name))
    df[column_name] = df[column_name].str[4:-4]

    #Fuction to insert condition type (Fast, Slow, Control) based on
the first letter of the particpants ID
    def map_condition(id_value):
        if id_value.startswith('H'):
            return 'Fast'
        elif id_value.startswith('L'):
            return 'Slow'
        elif id_value.startswith('C'):
            return 'Control'
        else:
            return 'Unknown'

    # #Create column C for the condition
    df['C'] = df['ID'].apply(map_condition)
    column_name = 'C'
    df.insert(1, column_name, df.pop(column_name))

    # #Determine whether particpants flow was GAMING -> READING or
READING -> GAMING
    if df['Stimuli'].iloc[0] == 'Game':
        df['S'] = 'GR'
    elif df['Stimuli'].iloc[0] == 'Reading':
        df['S'] = 'RG'
    else:
        df['S'] = 'Unknown'

    # #Create column S for the stimuli sequence
    column_name = 'S'
    df.insert(2, column_name, df.pop(column_name))
```

```
    df.reset_index(inplace=True, drop=True)

    # #Split dataframe in two (one for Gaming stimuli, one for Reading
stimuli)
    df_game = df[df['Stimuli'] == 'Game']
    df_read = df[df['Stimuli'] == 'Reading']

    # #Calculate preferred variables
    ID = df_game['ID'].max()
    condition = df_game['C'].max()
    sequence = df_game['S'].max()
    time_total = int((df['Timestamp'].max()-
df['Timestamp'].min())/1000)
    time_g = int((df_game['Timestamp'].max()-
df_game['Timestamp'].min())/1000)
    time_r = int((df_read['Timestamp'].max()-
df_read['Timestamp'].min())/1000)
    fixations_g = int(df_game['Fixation Index'].max()-
df_game['Fixation Index'].min())
    fixations_r = int(df_read['Fixation Index'].max()-
df_read['Fixation Index'].min())
    fixations = fixations_g+fixations_r
    fixations_minute = int((fixations/time_total)*60)
    fixations_r_minute = int((fixations_r/time_r)*60)
    fixations_g_minute = int((fixations_g/time_g)*60)
    duration_g = round(df_game['Fixation Duration'].mean())
    duration_r = round(df_read['Fixation Duration'].mean())
    duration = int((duration_g+duration_r)/2)
    pupil_g = round((df_game['ET_PupilLeft'].mean()
+df_game['ET_PupilRight'].mean())/2, 3)
    pupil_r = round((df_read['ET_PupilLeft'].mean()
+df_read['ET_PupilRight'].mean())/2, 3)
    pupil = round((pupil_g+pupil_r)/2, 3)

    new_row = [ID, condition, sequence, time_total, time_g, time_r,
fixations, fixations_g, fixations_r, fixations_minute,
fixations_g_minute, fixations_r_minute, duration, duration_g,
duration_r, pupil, pupil_g, pupil_r]
    eye.loc[len(eye)] = new_row

#Execute the cleaning function for all .csv-files in the folder (i.e.,
for all participants)
for filename in filenames:
    process_eye_file(filename)

#Replace ID (so that H1 becomes F1, 'Fast' instead of 'High')
def replace(text):
    if text.startswith('H'):
```

```
        return 'F' + text[1:]
    elif text.startswith('L'):
        return 'S' + text[1:]
    return text

# Apply the replace function to the column
eye['ID'] = eye['ID'].apply(replace)

#Print the resulting DataFrame
eye.head()
```

```
   ID        C   S  Total Time (sec)  Time_G (sec)  Time_R (sec)  \
0  F1     Fast  GR               472           241           203
1  S1     Slow  RG               534           241           232
2  C1  Control  GR               433           241           167
3  F2     Fast  GR               497           241           210
4  S2     Slow  GR               421           241           139

   Fixations (abs)  Fixations_G (abs)  Fixations_R (abs)  Fixations
(min)  \
0             1212                513                699
154
1             1201                469                732
134
2              923                430                493
127
3             1310                542                768
158
4              958                475                483
136

   Fixations_G (min)  Fixations_R (min)  Duration (ms)  Duration_G
(ms)  \
0                127                206            469
641
1                116                189            535
718
2                107                177            697
782
3                134                219            626
818
4                118                208            562
752

   Duration_F (ms)  Pupil   Pupil_G   Pupil_R
0              297  4.318     5.144     3.491
1              353  4.344     4.881     3.808
2              612  4.139     4.708     3.569
3              434  3.858     4.414     3.302
4              372  3.405     3.647     3.163
```

Demographics Data Cleaning

Underneath the .csv-file from Qualtrics (containing the participants's demographics) is processed. The following commands are executed:

1. Data is being imported as .csv.
2. Unnecessary columns are removed and some others are renamed clearly.
3. Likert scale answers are transformed into integers (strongly disagree = 1, strongly agree = 5)
4. Datatypes of columns are changed

```
#Determine file location
path = r'Demographics_May 13, 2024_12.24.csv'

#Import .csv file as DataFrame and skip the first rows of metadata
demo = pd.read_csv(path, skiprows=0)
demo = demo.iloc[2:]

#Drop unnecessary columns
demo = demo.drop(['StartDate', 'EndDate', 'Status', 'IPAddress',
'Progress',
        'Duration (in seconds)', 'Finished', 'RecordedDate',
'ResponseId',
        'RecipientLastName', 'RecipientFirstName', 'RecipientEmail',
        'ExternalReference', 'LocationLatitude', 'LocationLongitude',
        'DistributionChannel', 'UserLanguage', 'Gender_3_TEXT',
'Education_8_TEXT', 'Dyslexia', 'Dyslexia_4_TEXT'], axis=1)
demo.reset_index(inplace=True, drop=True)

#Replace Likert answers with its corresponding integer
demo.replace(to_replace={'(1) Strongly disagree': '1', '(4) Disagree':
'2', '(3) Neither agree nor disagree': '3', '(4) Agree': '4', '(5)
Strongly agree': '5'}, inplace=True)
#Rename Likert scales with keyword
demo.rename(columns={'Statements_1': 'Computers', 'Statements_2':
'Videogames', 'Statements_3': 'Concentration', 'Statements_4':
'No_concentration', 'Statements_5': 'Preference'}, inplace=True)

#Convert columns to datatype STR
columns_to_convert1 = ['ID', 'Gender', 'Language', 'Education']
demo[columns_to_convert1] = demo[columns_to_convert1].astype(str)

#Convert columns to datatype INT
columns_to_convert2 = ['Age', 'Computers', 'Videogames',
'Concentration', 'No_concentration', 'Preference']
demo[columns_to_convert2] = demo[columns_to_convert2].astype(int)

#Replace ID (so that H1 becomes F1, 'Fast' instead of 'High')
def replace(text):
```

```
    if text.startswith('H'):
        return 'F' + text[1:]
    elif text.startswith('L'):
        return 'S' + text[1:]
    return text

# Apply the replace function to the column
demo['ID'] = demo['ID'].apply(replace)

demo.head()
```

```
   ID  Age  Gender Language          Education  Computers  Videogames  \
0  F1   25    Male       No    Master's degree          3           3

1  S1   25    Male       No  Bachelor's degree          2           2

2  C1   27  Female      Yes    Master's degree          4           3

3  C2   25  Female       No    Master's degree          4           3

4  S3   26    Male       No    Master's degree          5           4


   Concentration  No_concentration  Preference
0              1                 5           2
1              1                 5           3
2              1                 4           2
3              1                 5           3
4              1                 4           1
```

Scale Data Cleaning

Underneath a .csv-file containing the participants's scale answers ((1) Paas' Mental Effort Scale and (2) Single Ease Question) and the stimuli control questions, are processed. The following commands are executed:

1. Data is being imported as .xlsx.

```
#Define file location
path = r'Answers.xlsx'

#Transform .xslx file into DataFrame
scales = pd.read_excel(path, skiprows=0)

#Replace ID (so that H1 becomes F1, 'Fast' instead of 'High')
def replace(text):
```

```
    if text.startswith('H'):
        return 'F' + text[1:]
    elif text.startswith('L'):
        return 'S' + text[1:]
    return text

# Apply the replace function to the column
scales['ID'] = scales['ID'].apply(replace)

scales.head()
```

	ID	Mental G	SEQ G	Mental R	SEQ R	Check 1	Check 2
0	F1	5	5	8	6	True	True
1	S1	3	3	8	6	True	True
2	C1	6	3	7	5	True	True
3	F2	5	3	7	6	True	True
4	S2	4	5	6	4	True	True

Final DataFrame

Merging the (1) eye tracking data, (2) demographics and (3) scale answers based on the column 'ID'

```
#Merging eye tracking data with demographics
pre_final = pd.merge(eye, scales, on='ID')

#Merging aforementioned result with scales
final = pd.merge(pre_final, demo, on='ID')
final.head()
```

	ID	C	S	Total Time (sec)	Time_G (sec)	Time_R (sec)	\
0	F1	Fast	GR	472	241	203	
1	S1	Slow	RG	534	241	232	
2	C1	Control	GR	433	241	167	
3	F2	Fast	GR	497	241	210	
4	S2	Slow	GR	421	241	139	

	Fixations (abs)	Fixations_G (abs)	Fixations_R (abs)	Fixations (min)	\
0	1212	513	699	154	
1	1201	469	732	134	
2	923	430	493	127	
3	1310	542	768	158	

```
4                958                  475                  483
136

   ...  Check 2  Age  Gender  Language          Education
Computers  \
0  ...     True   25    Male        No    Master's degree          3

1  ...     True   25    Male        No  Bachelor's degree          2

2  ...     True   27  Female       Yes    Master's degree          4

3  ...     True   24    Male        No    Master's degree          5

4  ...     True   23    Male        No    Master's degree          4


   Videogames  Concentration  No_concentration  Preference
0           3              1                 5           2
1           2              1                 5           3
2           3              1                 4           2
3           4              1                 4           2
4           2              5                 4           4

[5 rows x 33 columns]
```

Export CSV

```
#Exporting the DataFrame into .csv file
final.to_csv('dataset.csv', index=False)
print("DataFrame has been exported to 'dataset.csv'")

DataFrame has been exported to 'dataset.csv'
```

Appendix C

Reading Stimuli

Underneath the article, from The Guardian, used as stimuli for the reading task. Source: https://www.theguardian.com/environment/2024/apr/03/boom-in-mining-for-renewable-energy-minerals-threatens-africas-great-apes-aoe

Boom in mining for renewable energy minerals threatens Africa's great apes

Researchers applaud move away from fossil fuels but say more must be done to mitigate effects on endangered species

Up to a third of Africa's great apes are threatened by a boom in mining projects for minerals required for the renewable energy transition, new research shows.

An estimated 180,000 gorillas, bonobos and chimpanzees are at risk due to an increase in demand for critical minerals such as copper, lithium, nickel and cobalt, a study has found. Many of those minerals are required for clean energy technologies such as wind turbines and electric cars. Researchers say the boom in demand is driving destruction of tropical rainforests which are critical habitats for Africa's great apes.

"Africa is experiencing an unprecedented mining boom threatening wildlife populations and whole ecosystems," researchers wrote in the paper, published in Science Advances. Africa is home to an estimated 30% of the world's mineral resources, and substantial production increases in renewable energy are expected to drive up demand.

Mining harms apes through habitat loss, pollution and disease. It can also make habitats more accessible to hunters and farmers, as roads are carved into forest. More than two-thirds of primate species are already threatened with extinction.

"A shift away from fossil fuels is good for the climate but must be done in a way that does not jeopardise biodiversity," said lead researcher Dr Jessica Junker from the non-profit conservation organisation Re:wild. "In its current iteration it may even be going against the very environmental goals we're aiming for ... It is crucial for everyone to adopt a mindset of reduced consumption."

Understanding the net impact of mining for energy transition minerals on biodiversity is challenging. The climate crisis also threatens great apes, and clean energy technologies are important to avoiding the worst effects of global heating.

The paper – written in collaboration with researchers from the German Centre for Integrative Biodiversity Research and the Martin Luther University Halle-Wittenberg – used data on operational and pre-operational mining sites in 17 African countries and mapped areas where mining and high ape densities overlapped. It defined a buffer area of 10km around the mine as the area that would be directly affected and a 50km buffer for indirect impacts.

The paper found that the largest mining impacts on apes were in the west African countries Liberia, Sierra Leone, Mali and Guinea. In Guinea, more than 23,000 chimpanzees (83% of the population) could be directly or indirectly affected by mining activities.

Even the most ecologically sensitive areas are generally not protected. Unrelated to apes, the paper found that 20% of mining areas overlapped with regions that were considered unique for biodiversity, or labelled "critical habitats". Junker said: "Companies, lenders and nations need to recognise that it may sometimes be of greater value to leave some regions untouched to mitigate climate change and help prevent future epidemics."

Researchers said more could be done to mitigate mining's effects on endangered species. Mining companies are not required to make biodiversity data publicly available. It is possible that the impact of mining projects on great apes and other species is even higher than this paper found, according to the researchers.

Biodiversity offset schemes are typically developed to last as long as the mining project does, although impacts on great apes are permanent. "Mining companies need to focus on avoiding their impacts on great apes as much as possible and use offsetting as a last resort, as there is currently no example of a great ape offset that has been successful," said Dr Genevieve Campbell from the International Union for Conservation of Nature, who is also a senior researcher at Re:wild.

Appendix D

Consent Form

Underneath, a blank version of the *Qualtrics* consent form, prior to the experiment, can be found.

Consent Form

Please complete the form below by ticking the relevant boxes and signing on the line below.

- ☐ I confirm that I am 18 years of age or over.
- ☐ I confirm that the research project "**Eye Tracking during Digital Tasks**" has been explained to me. I have had the opportunity to ask questions about the project and have had these answered satisfactorily. I had enough time to consider whether to participate.
- ☐ I consent to the material I contribute being used to generate insights for the research project "**Eye Tracking during Digital Tasks**".
- ☐ I consent to eye tracking and screen recordings being used in this study as explained in the information sheet. I understand that I can request to stop recordings at any time.
- ☐ I understand that if I give permission, the eye tracking and screen recordings will be held confidentially so that only researcher Mike van Gils has access to the recordings. The recordings will be held in a secure password protected private University computer for up to two weeks after which they will be fully anonymized and the original securely destroyed. In accordance with the General Data Protection Regulation (GDPR) I can have access to my recordings and can request them to be deleted at any time during this period.
- ☐ I understand that my participation in this research is voluntary and that I may withdraw from the study at any time without providing a reason, and that if I withdraw any personal data already collected from me will be erased.
- ☐ I understand that my participation is not a requirement for my course, and that participating or not will not impact me.

- ☐ I consent to allow the fully anonymized data to be used in future publications and other scholarly means of disseminating the findings from the research project.
- ☐ I understand that the data acquired will be securely stored by researchers, but that appropriately anonymized data may in future be made available to others for research purposes. I understand that the University may publish appropriately anonymized data in appropriate data repositories for verification purposes and to make it accessible to researchers and other research users.
- ☐ I agree to take part in the above research project on "**Eye Tracking during Digital Tasks**".

Please fill in your name and the date below.

Full name ☐

Date (dd-mm-yyyy) ☐

Please sign below.

SIGN HERE

clear

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Appendix E

Demographics Survey

Underneath, a blank version of the *Qualtrics* demographics survey, after the experiment, can be found.

Demographics

What is your participant ID?

What is your age?

What is your gender?

- Male
- Female
- Other, namely:

Is English your native language?

- Yes
- No

What is your highest achieved or current level of education?

- High School
- Secondary vocation education (Dutch: MBO)
- Higher professional education (Dutch: HBO)
- Bachelor's degree
- Master's degree
- Advanced Graduate or PhD
- Other, namely:

Have you ever been diagnosed with dyslexia or other reading disabilities?

- No
- Yes, dyslexia.
- Other, namely:

Please rate the following statements on a scale from 1 - 5, with 1 being strongly disagree and 5 being strongly agree.

	(1) Strongly disagree	(4) Disagree	(3) Neither agree nor disagree	(4) Agree	(5) Strongly agree
I am skilled in using computers	○	○	○	○	○
I am skilled in playing video games	○	○	○	○	○
I often listen to music during tasks where concentration is needed (i.e. solving hard puzzles/math/reflective thinking)	○	○	○	○	○
I often listen to music during tasks where concentration is NOT needed (i.e. booking a trip, vacuum cleaning, drawing)	○	○	○	○	○
I prefer working/stuyding with music	○	○	○	○	○

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Appendix F

Ethics and Privacy Scan

The Ethics and Privacy Quick Scan of the Utrecht University Research Institute of Information and Computing Sciences was conducted (see below).

Ethics and Privacy Quick Scan

Section 1. Research projects involving human participants.

		Yes	No
P1	Does your project involve human participants? This includes for example use of observation, (online) surveys, interviews, tests, focus groups, and workshops where human participants provide information or data to inform the research. If you are only using existing data sets or publicly available data (e.g. from Twitter, Reddit) without directly recruiting participants, please answer no.	**X**	

If no, continue with Section 2; if yes, fill in the following questions.

Recruitment

		Yes	No
P2	Does your project involve participants younger than 18 years of age?		**X**
P3	Does your project involve participants with learning or communication difficulties of a severity that may impact their ability to provide informed consent?[1]		**X**
P4	Is your project likely to involve participants engaging in illegal activities?		**X**
P5	Does your project involve patients?		**X**

[1] For informed consent people need to be able to (1) understand information provided relevant to making the consent decision, (2) retain this information long enough to be able to make a decision, (3) weigh the information, (4) communicate the decision.

P6	Does your project involve participants belonging to a vulnerable[2] group, other than those listed above?		**X**

If the answer to all of P2-P6 is no, continue with P8.

⚠ **As you are dealing with vulnerable participants (yes to one (or more) of P2-P6) a fuller ethical review is required.** Please add more detail on your participants here:

		Yes	**No**
P7	Do you intend to be alone with a research participant or have to take sole responsibility for the participants at any point during your research activity?		

If P7 is no continue with P8, otherwise:

⚠ **As you will be alone with or solely responsible for vulnerable participants (yes to P7) a fuller ethical review is required. You may also need a Certificate of Conduct (Dutch: VOG) from the government.** Please add more detail here:

		Yes	**No**

[2] Vulnerable people include those who are legally incompetent, who may have difficulty giving or withholding consent, or who may suffer highly adverse consequences if their personal data were to become publicly available or from participating. Examples include irregular immigrants, sex workers, dissidents and traumatized people at risk of re-traumatization.

P8	Does your project involve participants with whom you have, or are likely to have, a working or professional relationship: for instance, staff or students of the university, professional colleagues, or clients?	**X**	

If the answer to P8 is yes, please answer P9, otherwise, continue with PC1.

		Yes	**No**
P9	Is it made clear to potential participants that not participating will in no way impact them (e.g. it will not directly impact their grade in a class)?	**X**	

If the answer to P9 is yes, then continue with PC1, otherwise:

As participants may think that not participating may harm them (yes to P8 and no to P9), participation may no longer be voluntary. Hence, a fuller ethical review is required. Please provide more information here:

Consent Procedures		**Yes**	**No**	**Not applicable**
PC1	Do you have set procedures that you will use for obtaining *informed* consent from all participants, including (where appropriate) parental consent for children or consent from legally authorized representatives? (See	**X**		

	suggestions for information sheets and consent forms on the website[3].)			
PC2	Will you tell participants that their participation is voluntary?	**X**		
PC3	Will you obtain explicit consent for participation?	**X**		
PC4	Will you obtain explicit consent for any sensor readings, eye tracking, photos, audio, and/or video recordings?	**X**		
PC5	Will you tell participants that they may withdraw from the research at any time and for any reason?	**X**		
PC6	Will you give potential participants time to consider participation?	**X**		
PC7	Will you provide participants with an opportunity to ask questions about the research before consenting to take part (e.g. by providing your contact details)?	**X**		

If the answer to PC1-PC7 is yes, then continue with PC8, otherwise:

Given your responses to the informed consent questions (a no on any of PC1-PC7), a fuller ethical review is required. Please provide more information regarding the questions that are causing this here:

[3] uu.nl/en/research/institute-of-information-and-computing-sciences/ethics-and-privacy

		Yes	No
PC8	Does your project involve concealment[4] or deliberate misleading of participants?		X

If the answer to PC8 no, continue with Section 2, otherwise:

⚠ As you plan to use concealment or misleading (yes to PC8), and this may impact participants' rights to informed consent, a fuller ethical review is required. Please provide more information on the concealment/misleading here:

Section 2. Data protection, handling, and storage

The General Data Protection Regulation imposes several obligations for the use of **personal data** (defined as any information relating to an identified or identifiable living person) or including the use of personal data in research.

		Yes	No
D1	Are you gathering or using personal data (defined as any information relating to an identified or identifiable living person[5])?	X	

If the answer to D1 is yes, please answer the following questions; otherwise, continue with Section 3.

High-Risk Data

[4] This may for example involve concealment of the study aim, of the identity of the researcher, or subliminal messaging during the study.

[5] This includes people's name, postal address, unique ID, IP address, voice, photo, video etc. When a person can be identified by combining multiple data points (e.g. gender + age + job role), this also constitutes personal data. When a person can be identified by a simple search online (e.g. with the content of a tweet) this also constitutes personal data. Note that Survey tool Qualtrics by default collects IP addresses and that the survey needs to be anonymized before distribution to prevent this.

		Yes	No
DR1	Will you process personal data that would jeopardize the physical health or safety of individuals in the event of a personal data breach?		**X**
DR2	Will you combine, compare, or match personal data obtained from multiple sources, in a way that exceeds the reasonable expectations of the people whose data it is?[6]		**X**
DR3	Will you use any personal data of children or vulnerable individuals for marketing, profiling, automated decision-making, or to offer online services to them?		**X**
DR4	Will you profile individuals on a large scale[7]?		**X**
DR5	Will you systematically monitor individuals in a publicly accessible area on a large scale[8] (or use the data of such monitoring)?[9]		**X**
DR6	Will you use special category[10] personal data, criminal offense personal data, or other sensitive personal data[11] on a large scale?		**X**

[6] This is about the combined use of data sets that have been gathered for different purposes (so not within one study), making the data more personal or sensitive. For example, combining participant data with religion or ethnic statistics data from the CBS based on zip code.
[7] Large scale is for example thousands of people, all visitors to a university website, data obtained over a very large time span
[8] Large scale is for example thousands of people, all visitors to the area, data obtained over a very large time span
[9] This may also include camera surveillance and use of drones
[10] Special category personal data is information about a person's health, ethnic origin, politics, religion, trade union membership, genetics, biometrics (where used in identification), sex life or sexual orientation.
[11] Other sensitive personal data includes for instance financial data (from which people's income, capital position or spending patterns can be derived), location data (from which people's movement patterns can be derived), achievement data (e.g. outcome of course work/exams, intelligence test; this excludes performance on tasks in a research study that are unrelated to their study/job), and communication data.

DR7	Will you determine an individual's access to a product, service, opportunity, or benefit[12] based on an automated decision or special category personal data?		**X**
DR8	Will you systematically and extensively monitor or profile individuals, with significant effects[13] on them?		**X**
DR9	Will you use innovative technology[14] to process sensitive personal data[15]?		**X**

If the answer to DR1-DR9 is no, continue with DM1, otherwise:

As high-risk data processing seems involved (yes to any of DR1-DR9), a fuller privacy assessment is required. Please provide more information on the DR1-DR9 questions with a yes here:

Data Minimization

		Yes	**No**
DM1	Will you collect only personal data that is strictly necessary for the research?	**X**	

If you answered yes to DM1 continue with DM4, otherwise:

		Yes	**No**
DM2	Will you only collect not strictly necessary personal data because it is (1) technically unfeasible not	**X**	

[12] Examples include: access to a mortgage, insurance, credit card, smartphone contract, course or degree programme, job opportunity.
[13] Significant effects are for example impacts on somebody's legal rights, automatic refusal of a credit application, automatic rejection for a job application.
[14] Innovative technology includes e.g. machine learning (including deep learning), neuro measurement (e.g. brain activity), autonomous vehicles, deep fakes, wearables, blockchain, internet of things.
[15] Sensitive personal data includes all data mentioned in DR6.

	to collect it when collecting necessary data[16], or (2) needed as a source of necessary data[17]?		
DM3	Will you (1) extract any necessary data as soon as possible from the collected not strictly necessary data and (2) delete the not strictly necessary data immediately after any required extraction?[18]	**X**	
DM4	Will you anonymize the data wherever possible?[19]	**X**	
DM5	Will you pseudonymize the data if you are not able to anonymize it, replacing personal details with an identifier, and keeping the key separate from the data set?	**X**	

If the answer to any of DM2-DM5 is no, see warning below, otherwise continue with DC1.

As you do not seem to minimize data collection (no to any of DM2-DM5), a fuller privacy assessment is required. Please provide more information on the DM2-DM5 questions with a no here:

<u>Using Collaborators or Contractors that Process Personal Data Securely</u>

[16] This may for instance occur when IP data is collected automatically in Qualtrics, and it is unfeasible not to do so as other personal data such as email needs to be collected.

[17] This may, for instance, occur when audio data is captured from which audio features need extracting or a transcript needs to be produced.

[18] This may for instance happen when you collect audio data, extract audio features or transcribe an audio interview as soon as possible, and delete the original audio recording once done.

[19] Possible also means given the research question. So, for example, if you have done interviews and you need to be able to at a later date link them to performance data, it is impossible to anonymize the interviews, and you will need to pseudonymize them. You can then answer yes to DM4 as you are anonymizing where it is possible, and yes to DM5 if indeed you pseudonymize. Note that in such a case you should anonymize once the linking has been done, destroying the key that links the pseudonym to the identity of the participant.

		Yes	No
DC1	Will any organization external to Utrecht University be involved in processing personal data (e.g. for transcription, data analysis, data storage)?[20]		**X**

If the answer to DC1 is yes, please complete DC2 otherwise continue with DI1.

		Yes	No
DC2	Will this involve data that is not anonymized?		

If the answer to DC2 is yes, please complete DC3-DC5, otherwise continue with DI1.

		Yes	No	Not Applicable
DC3	Are they capable of securely[21] handling data?			
DC4	Has been drawn up in a structured and generally agreed manner who is responsible for what concerning data in the collaboration?			
DC5	Is a written contract covering this data processing in place for any organization which is not another university in a joint research project?			

If the answer to any of DC3-DC5 is no, see warning below, otherwise continue with DI1.

[20] You can answer No if this is only the use of online software, as long as this software has been deemed safe by Utrecht University. See https://tools.uu.nl/tooladvisor/ for tools that are safe/not safe to use (e.g. Microsoft Word Online Transcribe is fine, NVivo Transcription is not).

[21] Secure handling includes for example: (1) only sharing data with those who legitimately need to see it, (2) data being securely stored on password-protected employer authorized IT systems (or in the case of non-digital data: in a secure locked location), (3) if portable devices such as USB sticks are used then only encrypted and password protected with data deleted as soon as it is no longer required to be portable, (4) reporting lost or stolen data immediately, (5) deleting or disposing of data as soon as it is no longer required and in a secure manner, (6) not discussing sensitive data in public places, (7) only carrying needed data when working off-site.

As you do not seem to have appropriate processes in place for sharing data with collaborators or contractors (no to any of DC3-DC5), a fuller privacy assessment is required. Please provide more information on the DC3-DC5 questions with a no here:

International Personal Data Transfers

		Yes	No
DI1	Will any personal data be transferred to another country (including to research collaborators in a joint project)?		X

If the answer to DI1 is yes, please complete DI2, otherwise continue with DF1.

		Yes	No
DI2	Do all countries involved in this have an adequate data protection regime?[22]		

If the answer to DI2 is no, please complete DI3, otherwise continue with DF1.

		Yes	No
DI3	Is a legal agreement in place?		

If the answer to DI2 and DI3 is no, see warning below, otherwise, continue with DF1.

As you do not seem to have appropriate safeguards in place for international data transfers (no to DI2 and DI3), a fuller privacy assessment is required. Please provide more information on intended international data transfers here:

Fair Usage of Personal Data to Recruit Participants

[22] Countries with an adequate data protection regime include EU countries, Andorra, Argentina, Canada (only commercial organizations), Faroe Islands, Guernsey, Israel, Isle of Man, Jersey, New Zealand, Switzerland, Uruguay, Japan, the United Kingdom, and South Korea.

		Yes	No
DF1	Is personal data used to recruit participants?[23]		**X**

If the answer to DF1 is yes please answer DF2-DF4, otherwise continue with DP1

		Yes	No	N/A
DF2	Have potential participants provided this personal data voluntarily to be contacted about the research or is the data publicly available?			
DF3	If contact details have been provided by a third party, would participants expect their details to be passed on to the university and to be used in this way?			
DF4	If contact details have been gathered for a purpose other than research, would participants expect their details to be used in this way?			

If the answers to DF2-DF4 are yes or N/A continue with DP1, otherwise:

[23] Intended here is the direct use of personal data to target a specific person. If you are using personal data indirectly to address a group of people, for example, sending a message via a *pre-existing* Microsoft Team, Blackboard course, Discord Channel, WhatsApp group, or crowd-sourcing platform, that is fine and will not be regarded as the use of personal data here. If you are asking friends or family members this will also not be regarded as use of personal data here.

⚠ **As there seem to be issues with your use of personal data for recruitment (no to one or more of DF2-DF4), a fuller privacy assessment is required.** Please provide more information on the intended use of personal data for recruitment here:

Participants' data rights and privacy information

		Yes	No	Not Applicable
DP1	Will participants be provided with privacy information? (Recommended is to use as part of the information sheet: For details of our legal basis for using personal data and the rights you have over your data please see the University's privacy information at www.uu.nl/en/organisation/privacy.)	X		
DP2	Will participants be aware of what their data is used for?	X		
DP3	Can participants request that their personal data be deleted?[24]	X		
		Yes	**No**	**Not Applicable**
DP4	Can participants request that their personal data be rectified (in case it is incorrect)?[24]	X		
DP5	Can participants request access to their personal data?[24]	X		
DP6	Can participants request that personal data processing is restricted?	X		
DP7	Will participants be subjected to automated decision-making based on their personal data with an impact on them beyond the research study to which they consented?		X	
DP8	Will participants be aware of how long their data is being kept for, who it is	X		

[24] This only concerns requests for personal data that you still hold. If you can no longer link the data to a participant due to anonymization, you can no longer delete, rectify or provide access to it. This should be clear to participants in the consent form. If the data is pseudonymized and you cannot access the key but the participant can (for example when the key is a WorkerID from a crowd-sourcing platform), participants should be able to request deletion on the provision of the key.

	being shared with, and any safeguards that apply in case of international sharing?			
DP9	If data is provided by a third party, are people whose data is in the data set provided with (1) the privacy information and (2) what categories of data you will use?	**X**		

If the answer to DP1-DP6, DP8, DP9 is yes and DP7 is no, continue with DE1, otherwise:

As there seem to be issues with the data rights of your participants or the provision of privacy information (no to one or more of DP1-DP6, DP8, DP9, or yes to DP7), a fuller privacy assessment is required. Please provide more detail regarding data rights and/or privacy information here:

Using data you have not gathered directly from participants

		Yes	No
DE1	Will you use any personal data[25] that you have not gathered directly from participants (such as data from an existing data set, data gathered by a third party, data scraped from the internet)?		**X**

If the answer to DE1 is no please continue with DS1.

		Yes	No
DE2	Will you use an existing dataset in your research?		

[25] Defined as any data related to an identified or identifiable living person. This includes people's name, postal address, unique ID, IP address, voice, photo, video etc. When a person can be identified by combining multiple data points (e.g. gender + age + job role), this also constitutes personal data.

If the answer to DE2 is yes please answer DE3-DE5, otherwise, continue with DE6.

		Yes	No
DE3	Do you have permission to do so from the owners of the dataset?		
DE4	Have the people whose data is in the data set consented to their data being used by other researchers and/or for purposes other than that for which that data set was gathered?		
DE5	Are there any contractual conditions attached to working with or storing the data from DE2?		

		Yes	No
DE6	Does your project require access to personal data about participants from other parties (e.g., teachers, employers), databanks, or files[26]?		

If the answer to DE6 is yes please answer DE7-DE8, otherwise, continue with DE9.

		Yes	No
DE7	Do you have a process in place to gain informed consent from these participants?		
DE8	Are there any contractual conditions attached to working with or storing the data from DE5?		

		Yes	No
DE9	Does the project involve collecting personal data from websites or social media (e.g., Facebook, Twitter, Reddit)?		

[26] For example, do you get a student's grade from the teacher, in addition to data gathered directly in your study or data in an existing research data set?

As there may be issues with the use of existing data (no to DE3, DE4, DE7 or yes to DE9), a fuller privacy assessment is required. Please provide more detail regarding the use of existing data here:

Secure data storage

		Yes	No
DS1	Will any data be stored (temporarily or permanently) anywhere other than on password-protected University authorized computers or servers?[27]		**X**

If the answer to DS1 is yes, please answer DS2, otherwise, continue with DS4.

		Yes	No
DS2	Does this only involve data stored temporarily during a session with participants (e.g. data stored on a video/audio recorder/sensing device), which is immediately transferred (directly or with the use of an encrypted and password-protected data-carrier (such as a USB stick)) to a password-protected University authorized computer or server, and deleted from the data capture and data-carrier device immediately after transfer?		

If the answer to DS2 is yes, continue with DS4, otherwise answer DS3.

[27] OneDrive business, Qualtrics, Microsoft Forms are ok. Do not use Google Drive/Sheets/Docs/Forms, Dropbox, OneDrive personal. See https://tools.uu.nl/tooladvisor/ for tools that are safe/not safe to use. Bachelor and master students are authorized to use a password-protected personal computer, as long as that computer is not shared with other people.

		Yes	No
DS3	Does this only involve data stored with a collaborator or contractor?		
DS4	Excluding (1) any international data transfers mentioned above and (2) any sharing of data with collaborators and contractors, will any personal data be stored, collected, or accessed from outside the EU[28]?		**X**

If the answer to DS2 and DS3 is no, or the answer to DS4 is yes, see the warning below, otherwise continue with Section 3.

⚠ **As there may be issues with secure data storage (no to DS2 and DS3, or yes to DS4), a fuller privacy assessment is required.** Please provide more detail regarding data storage here:

Section 3: Research that may cause harm

Research may harm participants, researchers, the university, or society. This includes when technology has dual-use, and you investigate an innocent use, but your results could be used by others in a harmful way. If you are unsure regarding possible harm to the university or society, please discuss your concerns with the Research Support Office.

		Yes	No
H1	Does your project give rise to a realistic risk to the national security of any country?[29]		**X**
H2	Does your project give rise to a realistic risk of aiding human rights abuses in any country?[30]		**X**

[28] This may happen, for instance, when data is collected and stored on a Utrecht University laptop whilst abroad.

[29] For example, research that can be used for autonomous armed vehicles/drones/robots, research on automated detection of objects, research on AI-enhanced forgery of video/audio data.

[30] For example, research on natural language/video/audio processing for automated identification of people's identity, sentiments, or opinions.

H3	Does your project (and its data) give rise to a realistic risk of damaging the University's reputation? (E.g., bad press coverage, public protest.)		**X**
H4	Does your project (and in particular its data) give rise to an increased risk of attack (cyber- or otherwise) against the University? (E.g., from pressure groups.)		**X**
H5	Is the data likely to contain material that is indecent, offensive, defamatory, threatening, discriminatory, or extremist?		**X**
H6	Does your project give rise to a realistic risk of harm to the researchers?[31]		**X**
H7	Is there a realistic risk of any participant experiencing physical or psychological harm or discomfort?[32]		**X**
H8	Is there a realistic risk of any participant experiencing a detriment to their interests as a result of participation?		**X**
H9	Is there a realistic risk of other types of negative externalities?[33]		**X**

If the answer to H1-H9 is no continue with Section 4, otherwise:

As you replied yes to one (or more) of H1-H9, a fuller ethical review is required. Please provide more detail here on the potential harm, and how you will minimize risk and impact:

Section 4: Conflicts of interest

	Yes	No

[31] For example, research that involves potentially violent participants such as criminals, research in likely unsafe locations such as war zones, research on an emotionally highly challenging topic, research in which the researcher is alone with a not previously known participant in the participant's home.

[32] For example, research that involves strenuous physical activity, research that stresses participants, research on an emotionally challenging topic.

[33] A negative externality is a harm produced to a third party, society in general, or the environment. For instance, intended or unintended negative ethical (e.g. bad governance or management practices), social (e.g. consumerism, inequality) or environmental effects (e.g. large CO2 footprint or e-waste production) of your project.

C1	Is there any potential conflict of interest (e.g. between research funder and researchers or participants and researchers) that may potentially affect the research outcome or the dissemination of research findings?		**X**
C2	Is there a direct hierarchical relationship between researchers and participants?		**X**

If the answer to C1-C2 is yes, continue with Section 5, otherwise:

⚠ **As you replied yes to C1 or C2, a fuller ethical review is required.** Please provide more information regarding possible conflicts of interest and how you mitigate them here:

Section 5: Your information

This last section collects data about you and your project so that we can register that you completed the Ethics and Privacy Quick Scan, sent you (and your supervisor) the summary of what you filled out, and follow up where a fuller ethics review and/or privacy assessment is needed. For details of our legal basis for using personal data and the rights you have over your data please see the University's privacy information. Please see the guidance on the ICS Ethics and Privacy website on what happens on submission.

Z0. Which is your main department?

○ Information and Computing Science

○ Freudenthal Institute

○ Pharmacy

○ Other, namely:

Z1. Your full name: **Mike (Emile) van Gils**

Z2. Your email address: m.e.vangils1@students.uu.nl / mikevangils1@gmail.com

Z3. In what context will you conduct this research?

○ 1. As a student on a course with course coordinator:

○ 2. As a student for my bachelor thesis, supervised by:

○ 3. As a student for my master thesis, supervised by: **Christof van Nimwegen**

○ 4. As a PhD student, supervised by:

○ 5. As an independent researcher (e.g. research fellow, assistant/associate/full professor)

In case the answer to Z3 is 2:

Z4. Bachelor programme for which you are doing the thesis:

○ Artificial Intelligence (Kunstmatige Intelligentie)

○ Computing Science (Informatica)

○ Information Science (Informatiekunde)

○ Other:

In case the answer to Z3 is 3:

Z5. Master programme for which you are doing the thesis:

○ Applied Data Science

○ Artificial Intelligence

○ Business Informatics

○ Computing Science

○ Data Science

○ Game and Media Technology

○ Human-Computer Interaction

○ Other:

In case the answer to Z3 is 1, 2, 3, or 4:

Z6. Email of the course coordinator or supervisor (so that we can inform them that you filled this out and provide them with a summary): c.vannimwegen@uu.nl

In case the answer to Z3 is 2 or 3:

Z7. Email of the moderator (as provided by the coordinator of your thesis project): graduation.hci@uu.nl

Z8. Title of the research project/study for which you filled out this Quick Scan:

Measuring the effects of music on cognitive load using eye tracking

Z9. Summary of what you intend to investigate and how you will investigate this (200 words max):

During this research the effect of background music on our cognitive load will be measured with eye tracking. Therefore, in the research proposal multiple variables and data are chosen to be collected. Firstly, participants will take place in the Human-Centered Computing Lab at UU. Here they will undergo the calibration of the eye tracking device (solely use of sensory systems, not physically attached to the body), followed with some digital tasks such as reading and gaming. During these tasks the eye tracking device will monitor their eye movement, capturing their gaze, fixation location, fixation duration, pupil dilation and blinking behaviour. Besides, the eye tracking device captures a screen recording where the eye movement are shown in combination with the real-time screen (i.e. seeing the cursor while playing the game). No camera recordings will be made of the participants.

Besides this data, a small questionnaire will be presented to the participants with questions about their experience and perceived difficulty/mental effort, together will basic demographics such as age, gender, education level etc.

In case the answer to Z3 is 2 or 3:

		Yes	No	Not Applicable
Z10.	In case you encountered warnings in the survey, does your supervisor already have ethical approval for a research line that fully covers your project?			**X**

In case the answer to Z10 is yes:

Z11. Provide details on the ethical approval (e.g. ethical approval number):
