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Finding the Perfect Beat: The Impact of Background Music Tempo and Personality on Gamified Learning Experiences

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Résumé

L’éducation STEM est souvent confrontée à des défis pour soutenir l’engagement et la motivation des apprenants en raison de sa difficulté perçue. Les techniques d’interaction homme-machine, dont la ludification, ont été utilisée pour rendre l’apprentissage des STEM plus agréable. Cependant, des stimuli ludiques complémentaires tels que la musique de fond sont peu étudiés dans les recherches sur la ludification. Cette thèse explore donc le rôle que la musique de fond pourrait jouer dans un contexte d’apprentissage STEM ludifié, intégrant les perceptions individuelles de ces stimuli, influencées par personnalité. En explorant l’intersection entre ludification, musique et personnalité, cette thèse espère rendre l’apprentissage STEM plus engageant et inclusif.

Une expérience intra-sujets a été menée à l'aide d'une plateforme gamifiée pour l'apprentissage des compétences en visualisation de données. Les participants (*n* = 59) ont chacun complété six tâches et ont été exposés à trois conditions de tempo de musique de fond : pas de musique, musique lente et musique rapide. Les tempos de musique de fond rapides augmentaient l'excitation, formant une relation non linéaire avec la performance. L'extraversion modère cette relation, permettant aux extravertis de tolérer plus d'excitation avant une baisse de performance. Sur la base de ces résultats, nous proposons également des applications pratiques pour les éducateurs et les concepteurs de logiciels qui souhaitent intégrer la musique dans leurs expériences d'apprentissage gamifiées.

Mots clés : musique de fond ; tempo ; activation; valence; extraversion ; ludification.

Méthodes de recherche : intra-sujets ; méthode quantitative ; régression linéaire ; ANOVA.

Abstract

STEM education is often challenged by keeping learners engaged and motivated due to its perceived difficulty. Human-computer interaction techniques, specifically gamification, have been employed to help make STEM learning more enjoyable. However, complementary stimuli in video games such as background music (BGM) have been understudied in gamification studies. This thesis thus explores the role BGM could play in a gamified STEM learning context, while also accounting for individual perceptions of such stimuli as coloured by personality traits. By investigating the intersection of gamification, music, and personality, this thesis hopes to make STEM learning more engaging and inclusive for all.

A within-subjects experiment was conducted using a gamified platform for learning data visualisation skills. Participants (n = 59) each completed six tasks and were exposed to three BGM tempo conditions: no music, slow music, and fast music. It was found that faster BGM tempi increased arousal, and arousal forms a non-linear relationship with performance. Extraversion moderates this relationship such that extraverts can tolerate higher levels of arousal before performance deteriorates. Based on these findings, we further suggest some practical applications for educators and software designers who wish to incorporate music in their gamified learning experiences.

Keywords: background music; tempo; arousal-mood hypothesis; extraversion; gamification.

Research methods: within-subjects; quantitative method; linear regression; ANOVA.

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List of Abbreviations and Acronyms

AMH – Arousal-Mood Hypothesis

AS – Affective Slider

BFI – Big Five Inventory

BGM – Background Music

BPM – Beats Per Minute

EDA – Electrodermal Activity

FFM – Five Factor Model

HCI – Human-Computer Interaction

LMM – Linear Mixed-Model

PBL – Points, Badges, Leaderboards

PFC – Prefrontal Cortex

SAC – SAP Analytics Cloud

SDT – Self-Determination Theory

STEM – Science, Technology, Engineering, and Mathematics

Foreword

This thesis consists of four chapters, including two articles: one scientific article and one managerial article. This has been submitted with approval from the Academic Affairs office of the Master of Science program. Chapter 2 of the thesis contains the scientific article. This article explores the effect of changes in background music tempo on the performance of learners completing a gamified STEM learning experience. The article is in preparation for submission to the journal *AIS Transactions on Human-Computer Interaction*. Chapter 3 of the thesis contains the managerial article which suggests practical recommendations for educators and game designers on the use of music in their gamified learning experiences. This article is also in preparation for submission to a journal to be identified.

The data collection process for this thesis has been approved by the Research Ethics Board of HEC Montréal, under the certificate number 2024-5934. Consent has been obtained from the co-authors for the inclusion of the scientific article found in Chapter 2.

Acknowledgements

I have never considered myself to be a “scientific” person, yet here I am, having completed a thesis for a Master of Science programme. It has been a journey of growth, patience, and fortitude, and I have many people to thank for helping me cross the finish line.

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Thank you to the Tech3Lab operations team for your training and invaluable support during the data collection process, and to the other members of the Tech3Lab for your insightful comments and discussions.

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Chapter 1
Introduction

Human-Computer Interaction (HCI) concerns itself with "the human and how to ensure that technology serves users' needs in the best possible way" (Stephanidis et al., 2019). In no other domain are these needs so apparent than in education, with "educational technology" being the most common field of discipline related to HCI in a literature review of 684 HCI-related journal articles published between 2001 and 2020 (Cho et al., 2021). Indeed, technology-mediated educational methods have become commonplace, though it is not in itself a panacea and has to be implemented well to have a positive effect (Henrie et al., 2015), as it has otherwise been linked to poor academic performance and higher dropout rates (Fredricks et al., 2004; Truta et al., 2018). This "positive effect" would refer to keeping learners engaged and motivated in learning – long a central concern in educational research. Improving student engagement can be approached in many ways, including creating a supportive environment, aligning pedagogical design with engagement goals, encouraging self-awareness in students, and improving teaching practices through active and collaborative learning (Kahu, 2013). To address these goals, gamification as an HCI-based technology mediation method has shown promise.

Gamification is the practice of using game design elements in non-gaming contexts (Deterding et al., 2011). This definition thus excludes "serious games" since they are still designed as full games but with educational content, notwithstanding their non-entertainment nature (Dichev & Dicheva, 2017). What gamification attempts to replicate in non-game contexts is not the playfulness found in games, but the "gamefulness", a concept introduced by McGonigal (2011). Deterding et al. (2011) defined "gamefulness" as embodying the ludic quality of gaming rather than the behavioural aspect of it, which is playfulness. Gamification then stems from “gamefulness” by using gameful design (taking game design elements) to encourage gameful interaction, which are the artifacts designed that create “gamefulness”. The simplest examples of gamification strategies include familiar elements such as points, badges, and leaderboards – typically known as the PBL trio (Bai et al., 2020). This may extend further to skill trees, competition, role play, and even health points, according to a literature review of 819 studies (Koivisto & Hamari, 2019).

Gamification has seen widespread attention in HCI, with a surge of research in the past decade (Trinidad et al., 2021) from just seven studies in 2012 to 917 by 2021 (Al-Hafdi & Alhalafawy, 2024). Positive effects have been found on user engagement, motivation, and performance (Li et al., 2023) across diverse applications, including healthcare (Sardi et al., 2017), software development (Cursino et al., 2018), and education, with education alone accounting for 42% of gamification research (Koivisto & Hamari, 2019). This can be attributed to gamification’s effects aligning well with education’s earlier-mentioned needs of sustaining engagement and motivation in a user (Sailer et al., 2017). Similarly, gamification and HCI more generally shares common theoretical ground with educational research through the self-determination theory (SDT). The SDT states that individuals are most motivated when they experience competence, connection, and autonomy in their actions (Deci et al., 1991). This theory is extensively used in in both gamification (Seaborn & Fels, 2015) and broader HCI studies (Tyack & Mekler, 2020), and education research (Deci et al., 1991), with both fields being concerned with motivation and more broadly, intervening on cognitive, emotional, and social levels (Landers et al., 2019).

It thus follows that the study of HCI and gamification have become integral to educational methods as they increasingly adopt technology. In the science, technology, engineering, and mathematics (STEM) fields where learners often struggle with engagement and motivation due to the subjects' technical nature (Du et al., 2016; Wolters, 2004), gamification may be particularly relevant in supporting and improving learning outcomes. To this end, gamification has been implemented in various STEM fields, such programming (Venter, 2020), engineering (Ortiz-Rojas et al., 2019), and data visualisation (Anderson et al., 2014; Legaki & Hamari, 2020). In particular, data visualisation has grown increasingly significant as the world becomes more data-driven (Naeem et al., 2022), making data literacy and proficiency in data visualisation software an essential skill for both current and future workers. As with most other gamification efforts, a review of 30 studies of gamified STEM experiences showed an overwhelming preference for the PBL trio, though other gamification elements used include characters, levels, bosses, virtual currencies, and experience points (Legaki & Hamari, 2020; Ortiz-Rojas et al., 2019).

From the above, gamification research tends to focus on the same game design elements at the expense of others. One such game design element, or at least a component of games, is music. There is generally a gap in music being researched as a stimuli in IS research (Gefen & Riedl, 2018), and even less so in gamification (Freitas et al., 2023). This is despite music having an acknowledged importance in games and being known to modulate performance in non-gaming domains. In games, music in the form of background music (BGM) is an invaluable tool for setting and enhancing the atmosphere (Klimmt et al., 2019; Ribeiro et al., 2020), immersion (Rogers et al., 2019), modulating emotion (Ganiti et al., 2018), changing behaviour such as risk-taking (Rogers et al., 2019), altering perceived stress (Schabert et al., 2023), and even gaming performance (Hufschmitt et al., 2020). In non-gaming contexts, different musical features have been shown to affect various facets of performance via the emotional dimensions of arousal and valence (Husain et al., 2002). Some of these features, as observed in a literature review of 49 studies, include tonality, loudness, tempo, and the presence of lyrics (Ho & Loo, 2023). Factors intrinsic to the listener may also be relevant in shaping responses to musical stimuli, such as personal genre preference (Rentfrow & Gosling, 2003), music familiarity (Kiss & Linnell, 2021), personality traits (Dobrota & Reić Ercegovac, 2015), and prior musical training (Nadon et al., 2021).

Music has such myriad effects on the individual due to its capability to induce specific brain responses, depending on a range of factors such as the genre and the musical feature (Ding et al., 2024). More specifically, music gets processed by the prefrontal cortex (PFC) of the brain in response to varying musical structures and features, which then translates to affective changes in arousal and valence as the PFC also functions as a brain's centre of emotional regulation (Koelsch & Siebel, 2005). For example, it was found that classical music, particularly with prolonged exposure, significantly activates the part of the PFC involved in higher cognitive functions such as decision-making and working memory rather than the part for emotional regulation (Bigliassi et al., 2015). Similarly, musical features such as harmony, rhythm, and timbre create different emotional impacts (Koelsch & Siebel, 2005). These neural effects of music, particularly those affecting emotional regulation, explains the heavy emphasis on arousal and valence in the literature as seen from Ho & Loo's (2023) review, as arousal and valence form the two dimensions of emotion (Russell, 1980), with arousal measuring the intensity of the emotion and valence the negative or positive nature of it. Arousal and valence here form a crucial link to learning, either by serving as an proxy of emotional engagement with the material (Charland et al., 2015), or a proxy of motivation (Harmon-Jones et al., 2013), both of which are elements crucial to a good learning experience.

Arousal and valence can be affected by various musical features, though the effects are not always in tandem. For instance, the presence of lyrics is disruptive and detrimental to performance as it generates cognitive load on the listener's part and increases arousal (Warmbrodt et al., 2022). Conversely, lyrics serve to amplify a piece of music's emotional perception, thus more clearly positively or negatively affecting valence (Juslin & Laukka, 2004; Mihalcea & Strapparava, 2012). Features of a piece of music specific to a listener, rather than the piece itself, are also relevant. For example, music familiarity forms an inverse relationship with arousal, such that moderate familiarity with a piece evokes the optimal level of arousal, whereas unfamiliarity and overfamiliarity leads to lower arousal (Chmiel & Schubert, 2017). Tempo is known to generally increase arousal levels the faster it is (Husain et al., 2002; van der Zwaag et al., 2011), though its relationship with valence is unclear. The literature on music's impact on affective states is varied and rich, with certain studies also further extending the theoretical scope by observing the impact of these affective changes on various forms of performance, such as spatial performance (Husain et al., 2002; Thompson et al., 2001), cognitive performance (Kumaradevan et al., 2021; Lin et al., 2023), general attention (Dovorany et al., 2023; McConnell & Shore, 2011), attentional control (Cloutier et al., 2020; Nadon et al., 2021), physical performance (Terry et al., 2020), and game performance (North & Hargreaves, 1999).

However, the musical experience does not exist in isolation as personality differences between listeners can colour the known effects. Personality refers to “the characteristics that are stable over time, provide the reasons for the person’s behaviour, and are psychological in nature” (Mount et al., 2005). A common model for studying personality traits is the Five-Factor Model (FFM), encompassing openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae & Costa, 1987). For music research, extraversion and neuroticism are the typically examined personality traits due to their interactions with arousal and valence. The FFM conception of extraversion is characterised by “lively sociability”, with extroverts being described as “sociable, fun-loving, affectionate, friendly, and talkative” (McCrae & Costa, 1987). The literature indicates that extraverts typically have a tolerance for heightened arousal (Eysenck, 1967), and in fact perform better at higher levels of arousal, with introverts experiencing the reverse (Geen, 1984) and in fact, seeming to possess a “shield” against overstimulation compared to introverts. This finding has been replicated in the context of cognitive test performance (Dobbs et al., 2011; Furnham & Strbac, 2002). On the other hand, neuroticism is characterised by descriptors such as “worrying, insecure, self-conscious, and temperamental”, with neurotic individuals being more prone to emotional instability (McCrae & Costa, 1987). Neurotic individuals tend to report higher valence after an extended music listening session, even if the session included sad music (Kallinen & Ravaja, 2004).

Similarly, personality also plays a part in gamified educational contexts. It significantly shapes learning experiences and outcomes, as different traits affect how students engage with the material and respond to behavioural interventions (Richardson et al., 2012), including to game design elements (Jia et al., 2016). Naturally, due to personality's effect on reactions to motivational and engagement affordances (Alexiou & Schippers, 2018), both gamification (Denden et al., 2024; Jia et al., 2016) and educational research (Richardson et al., 2012; Smiderle et al., 2020) have focused on it. In gamified learning environments, certain personality traits may make an individual less responsive to gamification. For example, a study which surveyed 248 participants in a gamified "Habit Tracker" application found that individuals with high emotional stability – corresponding to low neuroticism – are less affected by gamification generally (Jia et al., 2016) and thus, this trait is not a good indicator of the effectiveness of gamification. Conversely, extraversion has received particular attention due to its link to social and competitive elements such as leaderboards and points systems (Jia et al., 2016). As mentioned earlier, extraverts perform better at heightened arousal levels compared to introverts and thus seek more arousing activities. This can come in the form of social interaction (Zajonc, 1965), thus making extraverts respond more positively in terms of motivation and engagement to game design elements that involve competition or public recognition (Ashton et al., 2002).

Given that variance in neuroticism could weaken the effect of gamification and that extraversion is the common ground between music and educational gamification research, focusing on extraversion as an individual difference is the preferred path. This also frames arousal as a central variable to be examined, though valence remains important given the musical context. Returning to the initial issue at hand, technology has been increasingly employed as a way of ameliorating learning experiences, with HCI and gamification playing a central role in this. Among the various game design elements adopted, music is a separate stimulus that has largely been neglected in HCI and gamification research, and even more so in the education sphere. Thus, we pose two research questions.

RQ1: Does music help improve a learner's performance in a gamified STEM learning context?

RQ2: Does extraversion moderate this relationship between music and learner's performance in a gamified STEM learning context?

This thesis will attempt to answer these questions over the course of four chapters. Chapter 1 was this introduction, explaining the intersection of HCI and gamification, music, and personality. Chapter 2 presents a scientific article concerning a within-subject experiment observing the effect of changes in BGM tempo (no music as a control, slow music, fast music) on participants completing a gamified STEM learning experience. This chapter elucidates the theoretical frameworks the study uses, the methodology, then an analysis of the data gathered. The findings are discussed along with its theoretical contributions and practical implications, before diving into further areas of research. Chapter 3 contains a short managerial article for educators and software designers, providing some practical applications of the findings on using music in gamified learning experiences. These recommendations aim to provide educators with accessible ways to increase their students' engagement levels with the learning experience, especially if combined with gamification elements. For software designers, the recommendations hopefully provide some guidance for design decisions regarding the use of music. Finally, the thesis concludes with a summary and suggestions for future avenues of research in Chapter 4.

The following table details the contributions of the student in this thesis.

Table 1

Student's Responsibilities and Contributions to the Thesis

Stage	Contribution
Research Question	Identifying literature gaps, problematisation, and definition of research questions – **100%** - Comments from thesis co-supervisors
Literature Review	Conducting research by reading scientific articles concerning the problem and the constructs, writing of literature review – **100%**
Experimental Design	Experimental protocol – **80%** - Protocol section on tools set-up provided by Tech3Lab team ERPsim Business Builders (*Business Builders Software*, 2024) stimuli – **70%** - Existing prototype components created by ERPsim team used to fully design the stimuli Background music stimuli – **100%** Experimental questionnaire – **100%** CER application – **10%** - A large part of the application was already done by the Tech3Lab team
Data Collection	Pre-tests – **100%** Participant recruitment – 7**0%** - Recruitment done through HEC Panel and supplemented by word of mouth Data collection moderation – **100%**
Statistical Analysis	Data analysis – **90%** - Extraction of data from tools by Tech3Lab team - Advice sought from Tech3Lab statistician - Data treated and analysed by the student
Writing	Writing the thesis and its component articles – **100%** - Comments from thesis co-supervisors

Chapter 2:
The Impact of Background Music Tempo on Task Performance through the Lens of Arousal, Valence, and Extraversion[1]

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Abstract

Learning STEM skills is often a complex and challenging process, with learners frequently struggling to remain engaged and motivated. To alleviate this, technology has increasingly been used, drawing from the human-computer interaction domain to best cater technology-mediated educational methods to learners. More specifically, the use of game design elements – gamification – has become more popular. While some elements like leaderboards are commonly studied, stimuli such as background music (BGM) have been underexplored in gamification studies. BGM could play a crucial role in gamified learning due to its ability to affect the listener's performance through arousal and valence mechanisms. In considering BGM, this further calls for considering personality, as it may colour the perception of musical stimuli. To explore BGM's utility in a gamified context, a within-subject experiment on a gamified platform teaching data visualisation skills was conducted, observing the effect of BGM tempo on arousal and valence and then on

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[1] This article is in preparation for submission to the following journal: *AIS Transactions on Human-Computer Interaction*.

performance, with extraversion as a moderator. 59 participants were each exposed to three tempo conditions: no music as a control, slow music, and fast music, while completing six tasks. Following the arousal-mood hypothesis, we found that faster music increased self-reported arousal. This increased arousal forms a non-linear inversed U-shaped relationship with performance, with extraversion moderating this relationship. These findings reinforce the literature on the tempo-arousal-performance pathway, and on extraversion being a moderator of arousal. No significant relationships were found for valence.

Keywords: background music; tempo; arousal-mood hypothesis; extraversion; gamification.

2.1 Introduction

The field of Human-Computer Interaction (HCI) refers to the study of "the human and how to ensure that technology serves users' needs in the best possible way" (Stephanidis et al., 2019). HCI has found relevance in various fields, such as healthcare (Sardi et al., 2017), software development (Cursino et al., 2018), pilot training (Xiong et al., 2016), and education (Koivisto & Hamari, 2019). HCI is of particular importance to the educational field, where research has always sought to find the best ways to keep students engaged. This is because a lack of engagement can lead to poor academic outcomes, increased student boredom, and increased dropout rates (Fredricks et al., 2004; Truta et al., 2018). Simply using technology per se is insufficient, as online courses still see high dropout rates (Henrie et al., 2015). To counter this, gamification has been employed as a HCI strategy to increase engagement and motivation with learning experiences and thus, improve student performance (Fredricks et al., 2004).

Gamification, which is the use of game design elements in non-gaming contexts (Deterding et al., 2011), has been used to sustain engagement and motivation. Indeed, gamification research has been booming in the past decade (Hamari et al., 2014; Trinidad et al., 2021) and has been applied to many fields, though in particularly to education (Koivisto & Hamari, 2019). In education, gamification has proven to increase academic performance, engagement, motivation, and attention (Li et al., 2023; Subhash & Cudney, 2018). Common forms of gamification include points, badges, and leaderboards, though other forms such as levelling, avatars, and unlockable content are used too (Bai et al., 2020). Most research focus on the application of gamification in technical and abstract fields like information technology and mathematics (Dichev & Dicheva, 2017), where sustaining student engagement and motivation can be difficult due to the need for persistence and high avoidance from students with low self-efficacy (Wolters, 2004).

However, this is not to say that gamification is the miracle cure for improving learning outcomes. There have been conflicting results on the effectiveness of gamification, ranging from positive, to neutral, to even negative outcomes (Luo, 2022). Research may also be too focused on the trio of points, badges, and leaderboards at the expense of other game design elements and stimuli (Dichev & Dicheva, 2017; Li et al., 2023). One such stimuli is music (Freitas et al., 2023), where its potential use even in the information systems domain (Gefen & Riedl, 2018) remains understudied despite it being a key component of games (R. T. A. Wood et al., 2004) and its ubiquity and accessibility (North et al., 2004).

That said, the perceived musical experience can also be coloured by the individual's personality, with the Five-Factor Model (FFM) being a common framework for describing personality traits. Among these traits are extraversion and neuroticism, which are associated with music through their links to arousal and valence (Ho & Loo, 2023). Similarly, gamification also considers individual differences such as extraversion and neuroticism (Klock et al., 2020), with extraverts responding positively to social gamification with engagement and motivation (Ashton et al., 2002), and less neurotic individuals being less responsive to gamification generally (Jia et al., 2016).

Despite significant research in music, personality, and gamification, the intersection of these three areas is underexplored. While studies have commonly examined these areas in pairs, such as music and personality or personality and gamification, there is a lack of research integrating all three. This gap is particularly notable as these seemingly disconnected areas share the central variables of arousal and valence. Musical stimuli directly influence arousal and valence, personality traits such as extraversion modulate their effects, and gamification harnesses these effects to sustain engagement and motivation. By examining how music and personality interact to influence arousal and valence within a gamified context – which relies on these mechanism to enhance learning experiences – we can better understand their combined effects on learner performance. Thus, to address this gap and explore this intersection, we pose two research questions:

RQ1: Does background music tempo affect a learner's performance in a gamified STEM learning context through the mechanisms of arousal and valence?

RQ2: Does extraversion moderate this relationship between background music tempo and learner's performance in a gamified STEM learning context?

This study is grounded on two theoretical frameworks: the arousal-mood hypothesis (AMH) (Thompson et al., 2001) and Eysenck's theory of personality (Eysenck, 1967). The AMH suggests that music can influence arousal and valence, which, in turn, influence task performance. Eysenck's theory then posits that personality differences, particularly extraversion, may moderate the effect of arousal on performance. Combining these theories allows us to observe music's effect on performance through arousal and valence, while accounting for personality differences, of which extraversion will be examined to avoid neuroticism's possibility of reducing the effectiveness of gamification.

To answer the questions and implement the theoretical framework, this study used a gamified learning platform for teaching data visualisation and analytics skills: Business

Builders (*Business Builders Software*, 2024). The Business Builders platform presented participants with scenarios where they had to manipulate datasets to create graphs and charts to answer multiple-choice questions. Gamification came in the form of points, leaderboards, and a time limit of five minutes per question. A within-subject experiment was done where participants were exposed to three background music conditions: no music as a control, slow tempo, and fast tempo. Music tempo was chosen as the manipulation due to it being an easy musical dimension for a layperson to quantify. Instrumental classical music was used as the genre to avoid lyrics and because the genre presents a wide spectrum of tempo.

The study found that BGM tempo significantly increases arousal, which then significantly improves task performance up to a point before task performance starts to deteriorate. This relationship is moderated by extraversion, with extraverts requiring more arousal before task performance deteriorates. No significant relationship was found on the tempo-valence-performance track. Furthermore, incongruencies in significance were found between physiological and self-reported measures of arousal, with self-reported measures appearing more significant. Overall, the study confirms the literature on BGM tempo as a tool to improve task performance in a gamified setting, thus suggesting that BGM tempo manipulations could supplement gamification. However, care must be taken to cater to each student's personality.

2.2 Literature Review

Gamification

Gamification is defined as "the use of design elements characteristics of games in non-game contexts" (Deterding et al., 2011). This definition thus excludes not just games, but also “serious games” which though are for non-entertainment purposes, are still designed as full games (Dichev & Dicheva, 2017). Typical game design elements used would be the trio of points, badges, and leaderboards, or the “PBL” triad (Bai et al., 2020; Mazarakis, 2021). Other elements, as gathered from a literature review of 819 studies, include skill trees, competition, role play, and even health points (Koivisto & Hamari, 2019).

Gamification serves several purposes, with the most common ones being to intrinsically motivate the user, increase the user’s engagement with the experience, or to increase the user’s perceived usefulness of the experience (Koivisto & Hamari, 2019). Accordingly, the most common theories associated with gamification research include the self-determination theory and the flow theory (Zainuddin et al., 2020). The self-determination theory states that people are most motivated when they experience autonomy, competence, and relatedness in the actions they engage in (Deci & Ryan, 2000). Most gamification studies tend to draw upon the self-determination theory to investigate elements which could manipulate the motivation (Seaborn & Fels, 2015). As for the flow theory, a user reaches a state of “flow” when they experience complete engagement with the task, distortion of time, and intrinsic enjoyment of the process (Nakamura & Csikszentmihalyi, 2009). Similarly, gamification studies use the flow theory to promote active engagement and augment performance of the user with the task. Research on the PBL triad has shown the triad to increase motivation and engagement, leading to better learning performance (Zainuddin et al., 2020). Notably, leaderboards were singled out as being particularly effective as a gamification device in education by enhancing motivation via social connectivity, resulting in competition and comparison (Aldemir et al., 2018; Chang & Wei, 2016; Ortiz-Rojas et al., 2019).

Gamification in the Educational Context

Gamification has been applied in numerous contexts, including software engineering (Cursino et al., 2018; Kosa et al., 2016), crowdsourcing (Kapenekakis & Chorianopoulos, 2017; Morschheuser et al., 2017), healthcare (Edwards et al., 2016; Sardi et al., 2017), and most notably, education. In fact, a review of 462 full papers on gamification showed that 42% of the studies were in the domain of education (Koivisto & Hamari, 2019). While gamification has shown to be versatile in its applicability, its effectiveness depends on the elements used and the alignment with user needs and motivations. These needs may be attributed to factors such as individual personality differences (Jia et al., 2016; Smiderle et al., 2020), which has since led to growing interest in personalised and adaptive gamification methods to maximise engagement with users interacting with a gamified system (Hallifax et al., 2019).

In the context of education, gamification plays a valuable role in improving learning outcomes by enhancing motivation. Motivation is key to sustaining engagement, fostering positive attitudes, and encouraging the ability to overcome setbacks (Ames, 1992) and is thus strongly correlated to academic achievement (Linehan et al., 2011; Malone, 1981). The education field also strongly considers the effect of personality differences in learning as these differences can impact ideal learning styles and thus academic performance (Richardson et al., 2012). Similarly, when it comes to gamified learning using technology, gamification is essential for sustaining engagement and motivation (Santhanam et al., 2016) due to the high dropout rates of technology-assisted learning and the resulting learner disengagement (Greitzer et al., 2007). To aid this, gamification has the potential to be personalised to individual personality differences to enhance its effectiveness over one-size-fits-all gamification designs (Passalacqua et al., 2021; Santhanam et al., 2016) and indeed, over non-gamified learning generally. That said, while such common gamification elements exist, additional stimuli, such as music, may serve to augment a gamified experience.

Music as a Stimuli in Gamified Experiences

Some examples of gamification elements have been provided, and notably, music is not one of them. While not traditionally considered "gamification", it has been suggested that music should be investigated as a stimuli of interest in information systems studies due to its ability to affect stress levels and change user behaviours (Gefen & Riedl, 2018). Additionally, music plays a role of utmost importance in games, even if only subconsciously perceived by the player as BGM (R. T. A. Wood et al., 2004). It can influence the game's atmosphere (Ribeiro et al., 2020), and on the player's end, their flow state (Levy et al., 2015), their affective state (Klimmt et al., 2019), their motivation and stress levels (Schabert et al., 2023), their level of immersion (Rogers et al., 2019) and even performance (Hufschmitt et al., 2020). Thus, treating music as a stimuli that can be applied in gamified non-gaming contexts seems justified, given how it does have an impact on its listeners.

Music research is varied, given its various intrinsic facets, including tonality, the presence of lyrics, and loudness, among others (Ho & Loo, 2023). Music is also influenced by external factors, such as genre preference (Devenport & North, 2019; Vella & Mills, 2017), familiarity (Kiss & Linnell, 2021; Parente, 1976), and prior musical training (Liu et al., 2018; Nadon et al., 2021). Among the various intrinsic qualities of a piece of music is its tempo. Tempo has been manipulated in various contexts: as a distraction (Kallinen, 2002), in gaming (Ganiti et al., 2018), for motor skills (Arbinaga et al., 2020), for cognitive performance (Angel et al., 2010; Arboleda et al., 2022; Bottiroli et al., 2014; Hofbauer et al., 2024), and quite commonly, for emotion (Carpentier & Potter, 2007; Droit-Volet et al., 2013; Gomez & Danuser, 2007; Hunter et al., 2010; Liu et al., 2018, 2018; Trochidis & Bigand, 2013). Tempo is defined by its number of beats per minute (BPM) (London, 2002), with Milliman's (1982) study finding fast music to be at least 94 BPM, and slow music to be at most 72 BPM. It was chosen as this study's manipulation due to its ease of quantification and accessibility to the population in perception. While not intended to be a game design element, music could be used in the background to augment a gamified learning experience.

Furthermore, music research can be distinguished between investigating the emotional quality of the music and the emotions it induces and imparts on the listener, both corresponding respectively to the perceived emotion of the music and the experienced emotion from the music (Gomez & Danuser, 2007). The former involves the mechanism of the brain's prefrontal cortex responding to varying musical structures and features, resulting in changes in the emotional dimensions of arousal and valence (Koelsch & Siebel, 2005), both variables that feature heavily in music research (Ho & Loo, 2023). As such, emotion is induced in the listener and thus perceived. The latter, however, concerns the level of arousal and valence associated with the piece of music, which then gets transformed by the user's perception. Notably, these two emotions do not necessarily coincide as the listener, while aware of their perceived emotion, may not be aware of their "actual" experienced emotion defined by arousal and valence (Gabrielsson, 2001). Due to music being processed in the prefrontal cortex of the brain which also regulates emotions (Koelsch & Siebel, 2005), research on these relationships typically examine the two dimensions of emotion: arousal and valence (Russell, 1980).

Arousal, Valence and Performance

Together, arousal and valence form a two-dimensional framework of emotion as described by Russell's (1980) circumplex model of affect. Arousal is "a state of physiological activation or cortical responsiveness, associated with sensory stimulation and activation of fibres from the reticular activating system." (*APA Dictionary of Psychology*, n.d.-a), representing the intensity of the emotion ranging from deactivation to activation. Conversely, valence is "the value associated with a stimulus as expressed on a continuum from pleasant to unpleasant or from attractive to aversive." (*APA Dictionary of Psychology*, n.d.-b), representing the positive or negative nature of the emotion ranging from displeasure to pleasure. Thus, different emotions may be represented along the two dimensions which form emotional quadrants, such as excitement being in the high arousal and positive valence quadrant. Emotion is relevant as gamification can induce positive or negative emotions and correspondingly, affect motivation and engagement (Mullins & Sabherwal, 2020). It is through this lens of emotion that music could, as a stimuli, influence performance, through a framework called the arousal-mood hypothesis (Husain et al., 2002; Thompson et al., 2001) which will be elaborated upon in the next section. Some effects of music features on arousal and valence include the lyrics being disruptive to the listener and thus increasing cognitive load and arousal (Warmbrodt et al., 2022), a higher tempo inducing higher arousal (van der Zwaag et al., 2011), and lyrics serving to amplify a music's emotional perception, thus strengthening the positive or negative quality of its valence (Mihalcea & Strapparava, 2012). Through these changes in arousal and valence as induced by music, performance while doing a given task may be affected.

Performance as influenced by arousal and valence comes in various forms, such as cognitive performance (Hofbauer et al., 2024; Isen & Daubman, 1984), motor performance (Neiss, 1988), or even emotional performance in the form of emotional regulation (Gross, 1998). In gamified learning environments, cognitive performance is often the most relevant form, since individuals have to learn new information, apply the newly-acquired knowledge, and solve problems in real time (Kanfer & Ackerman, 1989). Similarly, this study concerns participants navigating a new interface to learn data visualisation skills which can be considered a difficult task due to its novelty (Yanagisawa, 2021), thus making cognitive performance the key indicator of performance. This learning experience can also induce various emotions, just as curiosity or frustration, thus modulating arousal and valence (Graesser & D'Mello, 2012). Various musical features can also affect performance. The literature shows that musical features, such as lyrics (Mihalcea & Strapparava, 2012), familiarity (Chmiel & Schubert, 2017), and tempo (van der Zwaag et al., 2011), are known to affect various facets of performance including spatial performance (Husain et al., 2002), cognitive performance (Kumaradevan et al., 2021; Lin et al., 2023), and game performance (North & Hargreaves, 1999). Thus, music can alter gamified learning experiences and could play potentially a role in improving STEM education. However, it must be noted that individual differences such as personality traits can colour the perception to both musical stimuli and game design elements. Thus, it is worth exploring how personality traits could interact with these stimuli.

Personality Traits

Personality is defined as “the characteristics that are stable over time, provide the reasons for the person’s behaviour, and are psychological in nature.” (Mount et al., 2005). One of the common models for classifying and measuring personality traits is the Five-Factor Model (FFM) which classifies personality using five dimensions: openness to experience, conscientiousness, extraversion, agreeableness, neuroticism (McCrae & Costa, 1987). Each of these dimensions may influence how an individual reacts to a certain gamification element, with extraversion and neuroticism particularly being of interest due to their interactions with arousal and valence in musical research (Ho & Loo, 2023). For example, extraverts, which are associated with sociability and friendliness (McCrae & Costa, 1989), can tolerate heightened levels of arousal, thus making their extraversion function as a “shield” against overstimulation (Eysenck, 1967). If anything, heightened arousal is beneficial and gets extraverts more “in the zone” to perform better, while introverts experience the opposite and suffer in performance instead (Geen, 1984). Neuroticism, which is characterised by emotional instability, tends to lend to stronger emotional responses and thus changes in valence to music (Kallinen & Ravaja, 2004).

Gamification research also explores extraversion and neuroticism when it comes to personality traits (Klock et al., 2020). For example, extraverts are known to respond well to game design elements that fit their social nature (Ashton et al., 2002) including the PBL trio (Jia et al., 2016). Regarding neuroticism, Jia et al’s (2016) study which surveyed 248 individuals on the use of various gamification elements for a “Habit Tracker” application found that individuals with low neuroticism (i.e. high emotional stability) were least affected by gamification generally. Considering this intersection between music and gamification, examining extraversion would be the better choice. First, gamification is less effective with less neurotic individuals, thus it is likely not an ideal personality trait in our context. Second, extraversion as a trait is highly linked to arousal, given their need for arousing activities to remain engaged (Eysenck, 1967). Arousal, taken with valence to form an affective state, could also serve as an indicator of emotional engagement (Boyle et al., 2012; Charland et al., 2015; Mekler et al., 2014), thus helping enhance the point of gamification. Arousal could even serve as a proxy of motivation (Harmon-Jones et al., 2013), yet another goal of gamification, through the use of points (Steinberger et al., 2017), and leaderboards and badges (Altmeyer et al., 2022). Finally, given that background music tempo will be manipulated in this experiment due to its accessibility to the general population, its known effects on arousal and extraverts further prompts the consideration of extraversion as a personality trait.

2.3 Theoretical Foundations and Hypotheses

The study is based on two theories: the arousal-mood hypothesis (AMH) (Thompson et al., 2001) and Eysenck's theory of personality (Eysenck, 1967). Within the framework of the AMH, it would be apposite to discuss further the existing empirical evidence of the effect of BGM tempo on arousal and valence, and the non-linear relationship between arousal and task performance which the AMH proposes.

The Arousal-Mood Hypothesis

The AMH finds its roots in the Mozart effect which claims that listening to music composed by Mozart directly improves spatial abilities due to certain neural activation patterns after listening to the music (Rauscher et al., 1993). However, this view was criticised by Husain et al. (2002) for discounting the observed effects of arousal and mood on performance. They suggested an alternative which posits a two-step relationship of a musical aspect affecting an individual's emotional arousal, mood, and enjoyment, all of which affect cognitive performance (Husain et al., 2002). In their experiment, individual participants were exposed to music manipulated by tempo (slow or fast) and mode (minor or major) before attempting a spatial task. It was found that faster music increased self-reported arousal whereas major-keyed music produced a more positive mood as measured through self-reported valence. Positive correlations were also found between arousal and mood with spatial task scores. More importantly, it was suggested that performance should not be limited to just spatial tasks and can be expanded to include cognitive performance. This has been done in further studies with performance being expanded to include outcomes such as increased selective attention (Cloutier et al., 2020), visual attention (Trost et al., 2014), and reading speed (Kallinen, 2002). While those studies were not conducted in the context of gamification and learning, music tempo might lead to better cognitive performance via arousal and mood during educational training.

The relationship between tempo and arousal is established, with the finding that faster tempi leads to increased arousal and slower tempi leads to decreased arousal (Droit-Volet et al., 2013; Husain et al., 2002; McConnell & Shore, 2011; Trochidis & Bigand, 2013; van der Zwaag et al., 2011), and faster tempi increasing skin conductance (Carpentier & Potter, 2007; Coutinho & Cangelosi, 2008; Gomez & Danuser, 2007). In comparison, tempo's effect on valence is less clear. In a seminal study proposing a framework for music's effect on arousal and mood, it was found that tempo does not affect mood (Husain et al., 2002). Though the AMH concerns mood, it corresponds well to valence as a measure according to the circumplex model of affect (Russell, 1980). This finding was replicated in later studies. For example, Gomez and Danuser's (2007) experiment exposed participants to 16 musical excerpts with 11 structural features, including tempo. Both physiological and self-reported measures of experienced arousal and experienced valence were recorded and the study found that while tempo affected arousal, it did not affect valence. However, other studies have shown the opposite. In Webster and Weir's (2005) study, participants were exposed to four musical phrases with variations of tempo, mode, and texture. Self-reported measures on valence were taken concerning how the musical phrase made the participant feel. It was found that valence increased linearly with tempo. Furthermore, a study which conducted a literature review of 49 studies to construct a theoretical framework linking arousal and valence to various facets of music, including tempo, uncovered no clear relationship between tempo and valence (Ho & Loo, 2023). This lack of clarity points to a gap in tempo's effect on valence which is worth examining.

Considering these findings, the AMH was adopted to explain the effect of BGM tempo on arousal and valence, and their effect on cognitive performance during a gamified learning experience. The manipulation is limited to tempo to isolate its effect on arousal and mood. As such, the hypotheses relating to arousal are:

H1a: Faster BGM tempo has a positive effect on physiological arousal.

H1b: Faster BGM tempo has a positive effect on self-reported arousal.

Given that there is no clear direction from the literature regarding tempo's effect on valence, it is hypothesised that:

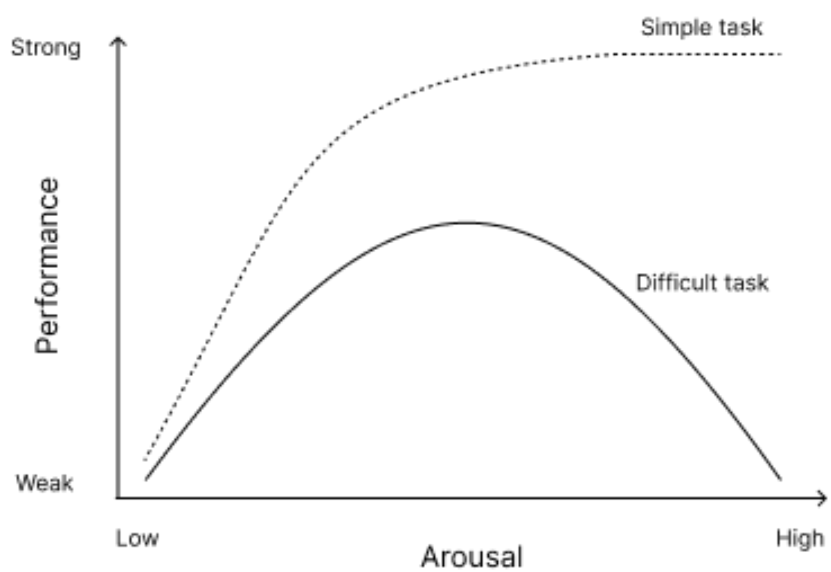
H2a: Changes in BGM tempo has an effect on physiological valence.

H2b: Changes in BGM tempo has an effect on self-reported valence.

For the second stage of the AMH, we observe the effect of the changes in arousal and valence on task performance. Between arousal and task performance, the literature presents two versions: a linear relationship for simple tasks and a non-linear relationship for complex tasks (Diamond et al., 2007; Yerkes & Dodson, 1908). As seen in Figure 1, as arousal increases during a difficult task, task performance increases up till a point where it is maximised. After this peak, any more arousal leads to reduced performance instead.

Figure 1

Relationships between Arousal and Performance Depending on Task Complexity



Note. Adapted from Diamond et al. (2007).

This phenomenon has been well-documented in the literature on the arousal-performance relationship over the years (Diamond et al., 2007; Easterbrook, 1959; Gilzenrat et al., 2010). In this study, we assume that the tasks are complex (Okuda et al., 2004; Sörensen et al., 2022; Yanagisawa, 2021) as participants learnt data visualisation skills using novel software. It is thus hypothesised that:

H3a: Increased physiological arousal has a positive effect on task performance up to optimal point before starting to deteriorate.

H3a: Increased self-reported arousal has a positive effect on task performance up to optimal point before starting to deteriorate.

Like the relationship between tempo and valence, the influence of valence on performance is also less clear. Some studies have interpreted the relationship to be linear, at least concerning various performance aspects such as cognitive processes influencing organisation (Isen & Daubman, 1984), and extrinsic and intrinsic motivation which then improve performance (Isen & Reeve, 2005). It was also found that positive valence may improve global information processing but impair narrower selective visual attention, though negative valence does not imply the opposite (Rowe et al., 2007). Yet, Fredrickson and Branigan (2005) could not replicate the finding on positive valence impairing narrower attention. Lastly, a study on task performance in the driving context found a non-linear relationship between valence and task performance, similar to the inverted U-shaped curve described by the Yerkes-Dodson law (Cai & Lin, 2011). It follows that there is no clear consensus on valence's impact on performance in the literature and again, this presents a gap which is worth examining in this study. Considering the conflicting conclusions found in the literature, we propose focusing on a more straightforward linear relationship between valence and task performance as a starting point for analysis, before delving into potentially more complex dynamics. The following hypotheses thus aim to contribute to a more coherent understanding of the valence and task performance relationship:

H4a: Increased physiological valence has a positive linear effect on task performance.

H4b: Increased self-reported valence has a positive linear effect on task performance.

Eysenck's Theory of Personality

According to Eysenck, individual personality differences have a basis in biology and the brain's central nervous system (Eysenck, 1967). Furthermore, these individual differences may be explained along three dimensions: extraversion-introversion, neuroticism-stability, and psychoticism-socialisation. Extraversion-introversion was theorised to affect cortical arousal levels.

Extroverts are theorised to have lower cortical arousal at rest than introverts and thus require more stimulating activities to reach the same arousal level as introverts (Eysenck, 1967). This has been confirmed in subsequent studies (Kumari et al., 2004; Matthews & Amelang, 1993). Additionally, there has been support for specifically BGM and noise having a different impact on performance between extroverts and introverts (Cassidy & MacDonald, 2007; Dobbs et al., 2011; Furnham & Strbac, 2002). In Cassidy & MacDonald's (2007) study, participants were exposed to four sound conditions (i.e. high-arousal music, low-arousal music, everyday noise, and silence) while completing five cognitive tasks, then self-reported their arousal and valence levels. It was found that introverts were more negatively affected by high-arousal music and noise compared to extroverts, thus aligning with Eysenck's theory that introverts get over-aroused more easily and that extroverts require more arousal to reach the same level as of introverts.

Thus, extraversion might moderate the relationship between arousal and performance in cognitive tasks like learning. This would suggest that the inversed U-shaped curve in Figure 1 may be displaced to the right for extroverts compared to introverts, following the notion that extroverts require more arousal to reach the optimal arousal level for performance. As found in Geen's (1984) study, over-stimulation impairs the performance generally, but only extroverts suffer in performance at lowered arousal levels. Additionally, it was found that introverts can function better at under-stimulated arousal levels than extroverts can at over-stimulated levels (Cassidy & MacDonald, 2007). Thus, it is hypothesised that:

H5a: Extraversion has a positive moderating effect on the relationship between physiological arousal and task performance.

H5b: Extraversion has a positive moderating effect on the relationship between self-reported arousal and task performance.

2.4 Methodology

A within-subjects experimental design was used for this experiment. BGM tempo was manipulated with three conditions: no music, slow music, and fast music. The no music condition served as the control condition. The experiment also included two other manipulations: video tutorial format and task complexity. The video tutorial format manipulation was a between-subjects manipulation with participants receiving either one long tutorial video before all tasks, or six short tutorial videos before each task. The task complexity manipulation was within-subjects with three conditions: easy, medium, and difficult. To account for these manipulations, participant conditions were counterbalanced to minimise their interference with the data gathered for this study's BGM tempo manipulation.

Sample Characteristics

Participants were screened with the following inclusion criteria: advanced written and spoken English; at least 18 years of age; have attained a qualification or is a student at the college, undergraduate, or post-graduate level; and have worked with graphs and tables during their studies. In total, 60 participants were recruited (*M* = 27, *median* = 26, *min* = 18, *max* = 65). Table 2 contains demographic information on the participants' gender and level of education. Gender was distributed almost evenly while two-thirds of the participants had at least a postgraduate level of education. One participant was not able to finish the experiment and thus, their data was excluded.

Extraversion was also measured for each participant in a post-test questionnaire. The values ranged between 1 to 7, with 7 being the most extroverted (*M* = 4.28, *median* = 4.25, *SD* = 1.34, *min* = 1.5, *max* = 7.0, *N* = 59). The distribution of participants by extraversion is close to normal, as presented in Appendix A.

Each participant was compensated $30 for their participation. They were generally recruited from Panel HEC and snowball sampling within the network. The study was approved by the research ethics board of HEC Montréal with the written consent of participants obtained at the time of the study, before starting the experiment (Certificate No. 2024-5934).

Table 2

Age and Education Level of Sample

	Frequency	Percentage
Gender		
Male	29	48%
Female	31	52%
Total	**60**	**100%**
Education Level		
CEGEP/College	4	7%
Undergraduate	16	27%
Postgraduate	40	66%
Total	**60**	**100%**

Experimental Manipulation

While our study used music in the background, Husain et al.'s (2002) application of the AMH had the music playing before the task. However, the AMH has been adapted for music played during tasks in subsequent studies (Cloutier et al., 2020; Nadon et al., 2021; Nguyen & Grahn, 2017; Palmiero et al., 2015) and has since become a way of applying the AMH in a significant number of studies (Ho & Loo, 2023).

For the BGM tempo manipulation, each participant was exposed to three conditions over six tasks: no music, slow music, and fast music. The beats per minute (BPM) to determine what constitutes slow and fast music was taken from previous literature, with slow music being 72 BPM and below, and fast music being 94 BPM and above (Dube & Chebat, 1995; Milliman, 1982). Each participant encounters each condition twice, and in pairs. This was done to prolong exposure to each condition to get a more accurate measurement for physiological arousal and valence. Both playlists were designed to last longer than ten minutes to ensure that there is enough music for the participant over each pair of tasks. Instrumental classical music was selected as the genre to avoid the presence of lyrics which could prove to be distracting (Avila et al., 2012). There were also more tracks for the fast music condition as each track tended to last a shorter amount time than tracks in the slow music condition. The tracks in each playlist are listed in Appendix B.

Experiment Stimuli

Each task consisted of two components to simulate the Business Builders game: a high-fidelity Figma mock-up of the "game" and SAP Analytics Cloud (SAC). On the Figma mock-up, each participant completes seven questions on the topic of international business expansion. The first question is a tutorial question to allow the participant to acclimatise to the platform and the remaining six being the actual tasks to be completed. For guidance on how to generate graphs and charts on SAC, participants were showed video tutorials before the task. SAC stores the dataset from which participants can generate graphs and visualise the data, allowing them to answer the questions found in the Figma mock-up. Screenshots of the Figma mock-up's flow and of the SAC platform's set-up can be found in Appendix B.

Instruments, Apparatus, and Lab Setup

Various instruments were used in the experiment. First, the Bluebox (Courtemanche et al., 2018), v0.5.0 was used to record electrodermal activity (EDA) and electrocardiogram activity. Noldus FaceReader (Noldus Information Technology bv, 2013), v9.0 was also used to review the facial expressions of participants recorded with a webcam during the tasks. Qualtrics (Qualtrics, 2005) was used to record self-reported measures. Detailed descriptions and photos of the participant and moderator setups can be found in Appendix C. A description of the experimental procedure is also found in Appendix D.

Measures

Arousal and valence were operationalised using both physiological measures and self-reported measures. These measures are key to obtain a fuller picture of arousal and valence. This allows us to capture not just objective and perceived experiences (Cacioppo & Berntson, 1994), but also to compare the continuous task experience through physiological measures and the post-task experience through the self-reports (van der Zwaag et al., 2011). A table mapping the variables to their names used in the data can be found in Appendix D.

Physiological arousal was measured using the Bluebox (Courtemanche et al., 2018) using EDA sensors as EDA has been found to be an indicator of it (Boucsein, 2012). A logarithmic transformation was done on the EDA data to normalise the distribution. The FaceReader software (Noldus Information Technology bv, 2013) was used to extract the facial expressions of participants as an indicator of physiological valence (Ekman & Friesen, 1982; van Kuilenburg et al., 2008). For self-reported arousal and valence, the Affective Slider (AS) was used to allow participants to self-report their arousal and valence levels post-task (Betella & Verschure, 2016). It consists of two continuous scales of 0 to 100 to easily measure emotional arousal and valence. The AS was intended to replace the traditional Self-Assessment Manikin for a quicker and more intuitive way to report arousal and valence. A strong correlation was found between both scales for both arousal (r = .85) and valence (r = .86) (Betella & Verschure, 2016).

Extraversion levels of each participant were recorded in the post-test questionnaire using the Big Five Inventory-10 (BFI-10) (Rammstedt & John, 2007), a truncated 10-question version of the full-length BFI-44 (John et al., 1991), of which two questions related to extraversion. The truncated BFI was used to save participants the burden of answering the full BFI-44 after completing an experiment. Furthermore, the extraversion dimensions of both BFIs have significant construct validity, with a part-whole correlation (r = .89), an external validity between self-reported and peer-rated scores (r = .57) and a test-retest reliability (r = .83) (Rammstedt & John, 2007).

Lastly, task performance was measured by task success rates, which were noted manually by the moderator in an observation grid. Each task required the participant to select the correct answer to the data visualisation question in the form of a multiple-choice question with three or four options. However, a task was considered successfully completed if the participant generated the appropriate graph on SAC to answer the data visualisation question within five minutes. If the participant accidentally selected the wrong answer on the Figma mock-up, it is still considered a success. In the dataset, failure is denoted by a 0 and success by a 1.

Data Analysis

Statistical analysis was done on SAS Studio (release 3.81, Enterprise version) accessed through SAS OnDemand for Academics. Data was collected from 59 participants. To test our hypotheses, linear mixed-effects models (LMMs) were used to account for the within-subjects experimental design where each participant is measured multiple times across tasks. Given that a two-stage research model with multiple relationships in each stage is used, separate LMMs are employed to fit each relationship. For the first stage of the research model, the within-subjects independent variable of BGM tempo (no music, slow, fast) is a fixed factor. For the second stage of the research model, the fixed factors are the within-subjects independent variables of arousal and valence, both physiological and self-reported measures. Since the arousal-performance relationship is hypothesised to be a non-linear relationship, arousal's quadratic term will be a fixed factor as well. Lastly, for the investigation of extraversion as a moderating factor on arousal's relationship with performance, the fixed factors will be arousal's linear and quadratic terms, extraversion, and the interactions between arousal's linear and quadratic terms with extraversion. Random intercepts were used to account for individual baseline differences between participants. Pairwise comparisons were corrected for multiple comparisons using Bonferroni correction.

2.5 Results

Descriptive Statistics

Table 3 contains the means, medians, and standard deviations of the success, arousal, and valence measures across all tempo conditions and the overall experiment. There are ten fewer sets of physiological arousal measures taken from the Bluebox EDA data due to equipment failure. This was random and did not appear to be connected to a specific period in the study, time of day, or the participant's demographic. As physiological arousal was log-adjusted, the values appear negative. However, values which are less negative and closer to zero are indicative of higher levels of physiological arousal. The median values of the task success rate across all conditions are 1.00 due to task success being a binary value, with 0 being failure and 1 being success. As more than half of the responses were successes, it follows that the median is 1.00 across all conditions.

Manipulation Check

Participants rated BGM tempo heard during each task on a Likert-type scale of 1 to 7, with 1 being the slowest speed and 7 being the fastest speed. No BGM was playing during the no music condition, but certain participants perceived there to be music and hence answered the question on tempo. Nevertheless, the statistics for the no music condition will still be reported for completeness. A one-tailed one-way ANOVA was done to examine the effect of the actual tempo conditions on the perceived tempo. The effect was significant ($F(2, 235) = 48.85$, $p < .0001$, $\eta^2 = 0.29$), pointing to actual tempo having a significant effect on perceived tempo overall. A pairwise comparison using Bonferroni correction showed that the mean perceived tempo for the slow-tempo condition ($M = 2.86$, $SD = 1.31$) was significantly lower than that of the fast-tempo condition ($M = 4.56$, $SD = 1.23$, $t(235) = 9.86$, $p < .0001$) and the no music condition ($M = 3.93$, $SD = 1.62$, $t(235) = 3.03$, $p = .0041$). There was no significant difference between the mean perceived tempo score for the fast-tempo condition ($M = 4.56$, $SD = 1.23$) and the no music condition ($M = 3.93$, $SD = 1.62$, $t(235) = 1.77$, $p = .12$).

Table 3

Descriptive Statistics of Success, Arousal, and Valence Measures across Tempo Conditions

Measure	*n*	No music			Slow			Fast			Overall		
		M	*Median*	*SD*	*M*	*Median*	*SD*	*M*	*Median*	*SD*	*M*	*Median*	*SD*
Task Success Rate	59	0.63	1.00	0.48	0.59	1.00	0.49	0.52	1.00	0.50	0.58	1.00	0.49
Arousal													
Physiological arousal	49	-3.36	-2.69	3.29	-3.47	-2.87	3.23	-2.67	-1.81	2.59	-3.17	-2.46	3.06
Self-reported arousal	59	63.03	65.00	17.81	59.34	61.00	20.80	65.60	65.60	20.98	62.66	64.50	20.03
Valence													
Physiological valence	59	-0.13	-0.13	0.12	-0.14	-0.13	0.13	-0.13	-0.12	0.14	-0.13	-0.13	0.13
Self-reported valence	59	57.55	57.50	20.25	51.48	53.00	20.78	54.70	56.00	21.18	54.58	55.00	20.83

Hypothesis Testing

<u>Tempo and Arousal</u>

One-tailed one-way ANOVAs were performed between tempo and arousal. Both physiological and self-reported measures of arousal were recorded to measure the actual and perceived experience. Tempo was found to have a significant overall effect on physiological arousal ($F(2, 168) = 4.99$, $p = .0039$, $\eta^2 = 0.056$). Post hoc comparisons using Bonferroni correction showed that the mean physiological arousal for the fast-tempo condition ($M = -2.67$, $SD = 2.59$) was significantly higher than that of the slow-tempo condition ($M = -3.47$, $SD = -2.87$, $t(168) = 3.05$, $p = .0041$) and that of the no music condition ($M = -3.36$, $SD = -2.69$, $t(168) = 2.24$, $p = .027$). Slow-tempo music ($M = -3.47$, $SD = -2.87$) did not show a significant change in physiological arousal compared to the no music condition ($M = -3.36$, $SD = -2.69$, $t(168) = -0.83$, $p = .20$). The fast-tempo condition showed a significant positive effect on physiological arousal compared to the no music and slow-tempo conditions. The results thus indicate that <u>**H1a** is supported</u> at a 5% significance level, specifically that fast music has a significantly positive effect on physiological arousal.

For self-reported arousal, the overall effect of tempo was significant ($F(2, 293) = 5.54$, $p = .0022$, $\eta^2 = 0.036$). Post hoc comparisons using Bonferroni correction showed that the mean self-reported arousal for the fast-tempo condition ($M = 65.60$, $SD = 20.98$) was significantly higher than that of the slow-tempo condition ($M = 59.34$, $SD = 20.80$, $t(293) = 3.31$, $p = .0016$). The fast-tempo condition ($M = 65.60$, $SD = 20.98$) did not have a significant difference on self-reported arousal from the no music condition ($M = 63.03$, $SD = 17.81$, $t(293) = 1.36$, $p = .088$). Similarly, the slow-tempo condition ($M = 59.34$, SD

= 20.80) also did not have a significant difference on self-reported arousal compared to the no music condition (*M* = 63.03, *SD* = 17.81, $t(293) = -1.95$, $p = .052$). Thus, the results indicate that **<u>H1b</u>** <u>is not supported</u>. Though not hypothesised but still related to the literature, it was found that slow music had a significantly negative effect on self-reported arousal.

<u>Tempo and Valence</u>

Two-tailed one-way ANOVAs were performed between tempo and valence. Both physiological and self-reported measures of valence were recorded to measure the actual and perceived experience. For physiological valence, the overall effect of tempo was insignificant ($F(2, 232) = 0.73$, $p = .49$, $\eta^2 = 0.0063$). Post hoc comparisons using Bonferroni correction also did not show significant differences in physiological valence between the slow-tempo condition (*M* = -0.14, *SD* = 0.13) and the fast-tempo condition (*M* = -0.13, *SD* = 0.14, $t(232) = 0.97$, $p = .81$). Considering the no music condition (*M* = -0.13, *SD* = 0.12), there were also no significant differences compared to the slow-tempo condition (*M* = -0.14, *SD* = 0.13, $t(232) = -1.10$, $p = .81$) nor to the fast-tempo condition (*M* = -0.13, *SD* = 0.14, $t(232) = -0.13$, $p = .90$). Thus, the results indicate that **<u>H2a</u>** <u>is not supported</u> as the overall effect of tempo on physiological valence was found to be insignificant.

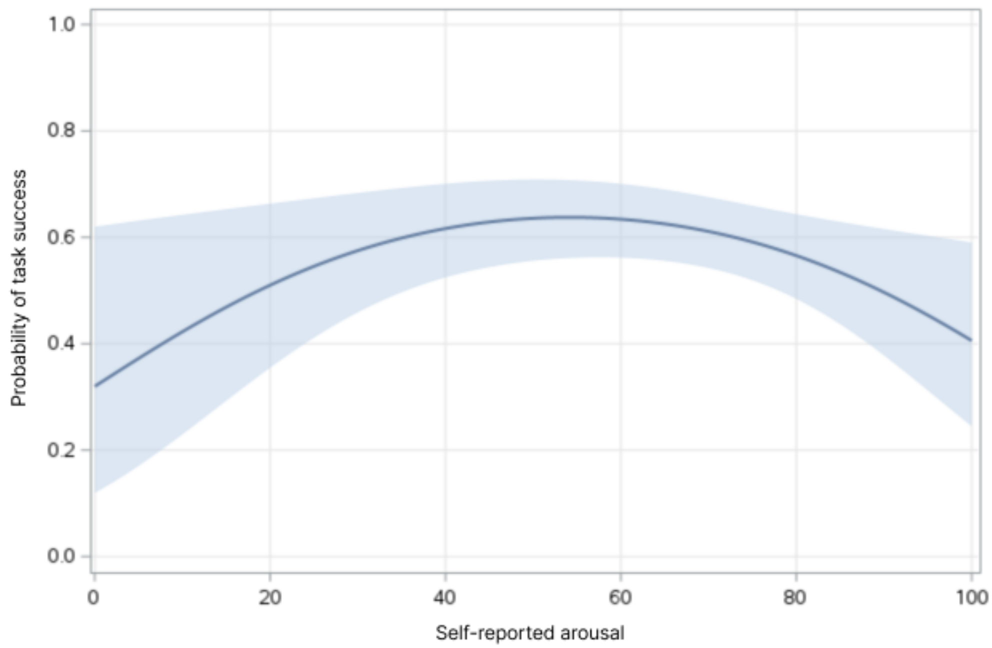
For self-reported valence, the overall effect of tempo was significant ($F(2, 293) = 3.05$, $p = .049$, $\eta^2 = 0.020$). Post hoc comparisons using Bonferroni correction showed that the mean self-reported valence for the slow-tempo condition (*M* = 51.48, *SD* = 20.78) was significantly lower than that of the no music condition (*M* = 57.55, *SD* = 20.25, $t(293) = -2.47$, $p = .043$). Conversely, there were no significant differences in self-reported valence between the slow-tempo condition ($M = 51.48$, $SD = 20.78$) and fast-tempo condition ($M = 54.70$, $SD = 21.18$, $t(293) = 1.31$, $p = .38$), nor between the no music condition ($M = 57.55$, $SD = 20.25$) and fast-tempo condition ($M = 54.70$, $SD = 21.18$, $t(293) = -1.16$, $p = .38$). However, based on the overall effect of tempo, it appears that **H2b** is supported, though finding significance only for slow music's negative effect.

Arousal and Task Performance

Two-tailed polynomial logistic regressions were conducted between both measures of arousal and task performance to determine the existence and significance of a non-linear relationship between physiological arousal and self-reported arousal respectively with task performance in the form of the probability of task success. Extraversion was added as a term but without an interaction effect. No significant relationship was found between physiological arousal and task performance ($\beta_2 = -0.023$, $SE\ \beta_2 = 0.012$, $OR = 0.98$, *95% CI* [0.95, 1.00], $p = .062$). Thus, **H3a** is not supported. For self-reported arousal, a significant quadratic effect was observed with task performance ($\beta_2 = -0.00046$, $SE\ \beta_2 = 0.00019$, $OR = 1.00$, *95% CI* [1.00, 1.00], $p = .015$), indicating that **H3b** is supported. Extraversion showed no significant effect on task performance. This points to a decrease in task performance after a certain point in self-reported arousal, as seen in Figure 2.

Figure 2

Predicted Probabilities Demonstrating a Non-Linear Relationship between Self-Reported Arousal and Probability of Task Success



Note. The blue shaded area represents the 95% confidence interval. The fit was computed at extraversion = 4.29.

Additionally, a simple slope analysis was done to examine the relationship between specific levels of self-reported arousal and the probability of task success, as seen in Table 4. This was done to provide more nuance to the generalised curve found in Figure 2 and to investigate the implications of its statistical significance contrasted with its practical insignificance seen from its effect size, odds ratio, and 95% confidence intervals.

Table 4

Simple Slope Analysis of Task Success Probabilities at Levels of Self-reported Arousal

Arousal level	β	SE β	Odds Ratio	95% CI (Lower)	95% CI (Upper)	p
10	0.15	0.60	1.16	0.36	3.74	.80
30	0.79	0.47	2.19	0.87	5.51	.096
50	1.05	0.45	2.86	1.18	6.92	.021*
70	0.94	0.44	2.57	1.08	6.14	.034*
90	0.47	0.48	1.60	0.62	4.10	.33

Valence and Task Performance

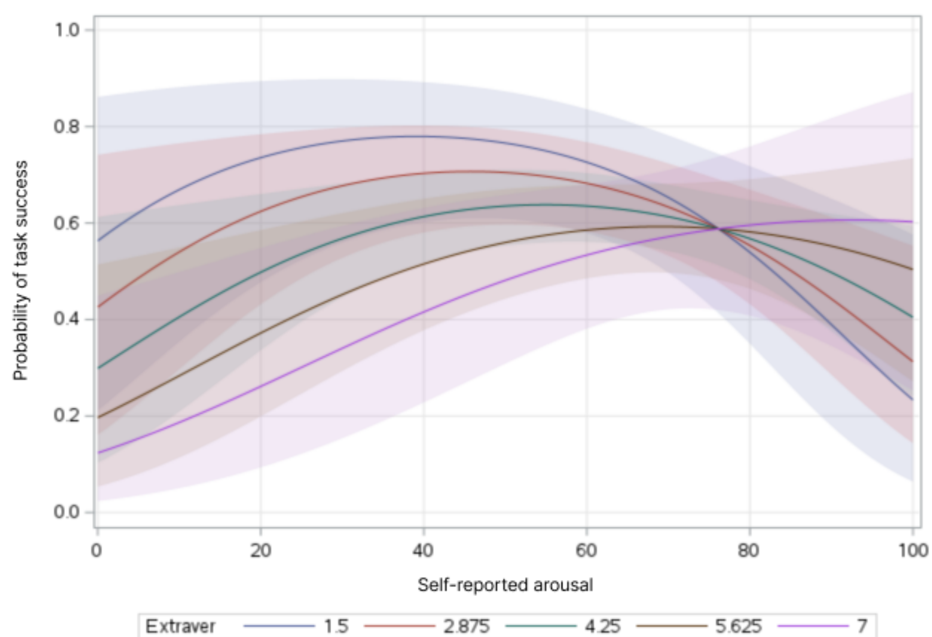
One-tailed linear regressions were conducted between physiological valence and task performance, and between self-reported valence and task performance. No significant relationship was found between physiological valence and task performance ($\chi^2(1) = 0.59$, $p = .44$). Thus, **H4a** is not supported. Conversely, self-reported valence was found to have a highly significant effect on task performance ($\chi^2(1) = 64.03$, $p < .0001$), with it being positively associated with task performance ($\beta = 0.064$, $SE\ \beta = 0.008$, $t(294) = 8.00$, $p < .0001$). This indicates that **H4b** is supported.

Extraversion as a Moderator of Arousal

One-tailed polynomial logistic regressions were done between both measures of arousal separately with task performance, with extraversion as an interaction term to determine its moderating effect on both measures of arousal. There were no significant interactions found between physiological arousal and task performance (β_4 = 0.00055, *SE* β_4 = 0.0050, *OR* = 1.00, *95% CI* [0.99, 1.01], *p* = .46), indicating that **H5a** is not supported. Conversely, there was a significant interaction effect between the quadratic term for self-reported arousal and extraversion (β_4 = -0.000069, *SE* β_4 = 0.000038, *OR* = 1.00, *95% CI* [1.00, 1.00], *p* = .034). Thus, **H5b** is supported, showing that the non-linear relationship between self-reported arousal and task performance is moderated by extraversion, and thus the optimal point of arousal shifts according to the level of extraversion. This is seen in Figure 3, where different extraversion levels have different curves showing the predicted probabilities of task success at various levels of self-reported arousal. Table 5 below provides a summary of all hypotheses discussed in this section.

Figure 3

Predicted Probabilities of Task Success against Self-Reported Arousal and Extraversion



Note. The coloured shaded areas around each curve represent the 95% confidence interval.

Table 5

Summary of Results

	Hypothesis	*p*	Supported?
H1a	Faster BGM tempo has a positive effect on physiological arousal.	Slow: .20 Fast: .013*	Yes
H1b	Faster BGM tempo has a positive effect on self-reported arousal.	Slow: .026* Fast: .088	No
H2a	Changes in BGM tempo has an effect on physiological valence.	Slow: .14 Fast: .45	No
H2b	Changes in BGM tempo has an effect on self-reported valence.	Slow: .0071* Fast: .12	Yes
H3a	Increased physiological arousal has a positive effect on task performance up to optimal point before starting to deteriorate.	.062	No
H3b	Increased self-reported arousal has a positive effect on task performance up to optimal point before starting to deteriorate.	.015*	Yes
H4a	Increased physiological valence has a positive linear effect on task performance.	.22	No
H4b	Increased self-reported valence has a positive linear effect on task performance.	<.0001***	Yes
H5a	Extraversion has a positive moderating effect on the relationship between physiological arousal and task performance described in H3.	.46	No
H5b	Extraversion has a positive moderating effect on the relationship between self-reported arousal and task performance described in H3.	.034*	Yes

2.6 Discussion

The objective of the study was to observe the effect of BGM tempo on task performance in a gamified learning context through the lens of the AMH (Husain et al., 2002; Thompson et al., 2001). The AMH separates the analysis into two steps: the effect of tempo on arousal and valence, and the effect of these changes in arousal and valence on task performance. To account for personality differences, extraversion was also considered to discover how it relates to arousal and task performance, as described by Eysenck's theory of personality (Eysenck, 1967). To this end, an experiment was conducted where participants had to complete six tasks in a gamified learning setting while having BGM of varying tempos played over speakers. The pairwise comparisons confirmed that the slow music manipulation was rated to be significantly slower than the fast music manipulation.

The Arousal-Mood Hypothesis

Based on the AMH and the existing literature, it was hypothesised that an increase in tempo would lead to a significant increase in both arousal (Droit-Volet et al., 2013; Gomez & Danuser, 2007; McConnell & Shore, 2011; van der Zwaag et al., 2011) and valence (Hunter et al., 2010; Liu et al., 2018; Trochidis & Bigand, 2013; Webster & Weir, 2005), which then affects task performance. The results partially corroborated previous findings. Key findings include a split in significance between physiological and self-reported measures for both arousal and valence; and significant effects found for the arousal route but not the valence route.

For arousal, it was found that an increase in tempo leads to a significant increase in physiological arousal for fast music but not for slow music, which matches the literature on fast-tempo music increasing skin conductance level (i.e. EDA), a measure specifically for physiological arousal (Coutinho & Cangelosi, 2008; Gomez & Danuser, 2007). While no statistically significant increase in self-reported arousal was found, there was still marginal significance which indicates a trend towards a significant relationship between tempo and arousal generally. The added finding of slow tempo significantly decreasing self-reported arousal, though not hypothesised, matches previous literature as well (Husain et al., 2002; McConnell & Shore, 2011). That said, a slower tempo did not significantly decrease self-reported arousal. Thus, the findings validate **H1a** in that faster BGM tempo induces heightened physiological arousal, but not for self-reported arousal described in **H1b**. This will be discussed later in the methodological implications of the study.

A non-linear quadratic relationship was also found between self-reported arousal and task performance in the form of the probability of task success, validating **H3b**'s hypothesis of such a relationship and corroborating the existing literature on such a relationship in the context of music (Geen, 1984; Hallam et al., 2002). This also fits the AMH's conception of the arousal-performance relationship as one following the Yerkes-Dodson law – an inversed U-shaped relationship as seen in Figure 1 (Husain et al., 2002; Yerkes & Dodson, 1908). Again, we see that significance was found only for one measure of arousal, self-reported arousal, but not physiological arousal. However, it must be noted that physiological arousal's effect on task performance described by **H3a** was still found to be marginally significant. Thus, the findings still point to a trend of a non-linear quadratic relationship between arousal and task performance.

However, caution must be given in attributing importance to the finding of this non-linear quadratic relationship between self-reported arousal and task performance. Given the overall model's odds ratio of almost one and the minuscule effect size of almost zero (Maher et al., 2013), the practical significance of the relationship is questionable, notwithstanding the statistical significance. That said, examining the relationship at specific levels of arousal reveals more. In Figure 4, it is seen that the confidence intervals are wider at the ends of arousal and narrower at a moderate level of self-reported arousal, indicating greater uncertainty. Table 3 shows that at extreme ends of arousal (i.e. 10, 30 and 90), the relationship is statistically insignificant. However, significance is still found at the mid ranges of 50 and 70, including odds ratios close to 3 that indicate a strong positive association (Hosmer Jr et al., 2013). It should also be noted that even though the arousal level of 30 is statistically insignificant, it still reaches the point of marginal significance with an odds ratio of above 2. Taken together, this fits the inversed U-shaped curve that was hypothesised and the AMH's reference to the Yerkes-Dodson law's theory of performance peaking at a moderate level of arousal.

For the valence branch of the arousal-mood hypothesis, findings were generally insignificant. Between tempo and valence, tempo had no significant effect on physiological valence at all. However, there was a significant relationship found between slow music and self-reported valence. Though this is consistent with literature finding that slower tempo was associated with lower valence (Hunter et al., 2010), the finding of insignificance between fast music and self-reported valence suggests that self-reported valence does not increase with tempo, going against the finding of a linear relationship (Webster & Weir, 2005). It follows that **H2** is rejected entirely as neither measure of valence was significantly affected by tempo changes. However, this does not mean that the AMH is called into question, as the associated study manipulated both tempo and mode and found that mode affected valence. Instead, this study adds on to the pool of literature confirming that music tempo per se has no significant effect on valence.

For **H4b**, though there was a highly significant relationship between self-reported valence and task performance, it is posited that this is not an accurate reflection of valence's effect upon task performance even if the question asked participants how they felt during the task. Participants reported their valence right after learning if they succeeded in the task which would have likely influenced their immediate emotional state based on their success rather than the BGM listened to. Additionally, there was no significant relationship found between physiological valence – which was measured during the task – and task performance. Thus, though the self-reported valence and performance relationship seems to validate **H4b**, the hypothesis should be rejected and thus, it appears that valence has no significant relationship with task performance at all.

Eysenck's Theory of Personality

As in **H5b**, extraversion was found to have a significant moderating effect on self-reported arousal's effect on task performance in the form of the probability of task success. First, as seen in Figure 5, the optimal point of arousal for each level of extraversion shifts. Less extroverted individuals reach their peak performance at a lower level of arousal, whereas more extroverted individuals require a higher level of arousal to reach their peak. Second, the shape of each curve, regardless of extraversion level, corroborates with the inversed U shape as hypothesised and confirmed in **H3**, with a clear optimal arousal point and a rise before and fall after the peak. Additionally, though not hypothesised, Figure 5 confirms Geen's (1984) finding that introverts function better at under-stimulating arousal levels compared to extroverts at over-stimulating arousal levels.

However, like **H3b**, though the overall model is statistically significant, it is again of limited practical significance due to its small effect of almost 0 and odds ratio of 1. The significant overlap in confidence intervals for each level of extraversion could also indicate a lack of meaningful difference (M. Wood, 2005). That said, this does not necessarily mean that the overall model is not applicable, as individuals on extreme ends of the extraversion spectrum may still react differently to different levels of self-reported arousal.

Theoretical and Methodological Contributions

The study confirmed the relationship between music tempo, arousal, and task performance within the AMH framework. It showed that music tempo does affect arousal, be it a negative relationship with slower tempi or a positive relationship with faster tempi, thus conforming with prior literature. It also partially confirmed the existence of a non-linear quadratic relationship between arousal and task performance, as the finding was found only for self-reported arousal. For valence, the study confirmed that music tempo changes do not have significant effects on valence, matching Husain et al.'s (2002) finding and adding to the literature confirming this. Lastly, aside from self-reported valence's highly significant relationship with task performance, which was interpreted as a post-task bias, there was no significant relationship found between valence and performance. This finding adds further to the plethora of conclusions found in the literature on the valence-performance relationship, shifting the balance towards a finding of non-significance.

The study also highlighted the importance of individual personality differences in adding nuance to an experiment. The study was able to confirm Eysenck's theory of personality regarding extraversion and thus enrich the application of the Yerkes-Dodson law in a gamified learning context with music as a stimuli. More importantly, it confirmed that regardless of extraversion level, the Yerkes-Dodson law applies and thus, different individuals will have differing requirements to achieve an optimal state of arousal and thus, performance.

Regarding methodology, this study highlights the importance of having both physiological and self-reported measures to get a fuller picture. Indeed, though self-reports have been described as "the only way to access subjective emotional experiences" (Gabrielsson, 2001), physiological measures are equally valuable for observing changes before the subjective emotional experience becomes salient (Gendolla, 2000; van der Zwaag et al., 2011). Additionally, the measures need not necessarily agree as emotion (arousal and valence, in this case) is not a one-dimensional construct (Cacioppo & Berntson, 1994; Mauss & Robinson, 2009). However, care must be taken in interpretation as the two measures cannot always be equated even if measuring the same variable. The time of measurement is important, as seen in the stark contrast between the highly significant self-reported valence-performance relationship and the insignificant physiological valence-performance relationship.

It was also seen in the data analysis that weight must be given to the effect sizes of a statistically significant finding, as that will affect the practical significance of the relationship. A small effect size is not necessarily a "negative" finding, as it may indicate an opportunity for further research with a different or larger sample to examine if the effect size changes. However, within the limited scope of one experiment, statistical significance should still be interpreted with caution considering minimal practical significance.

Practical Implications

The findings from this study suggest that BGM could be incorporated into gamified learning experiences to alter the arousal levels of learners and thus, their engagement levels (Charland et al., 2015). This could be used by educators in both technology-mediated learning experiences and those without technology used, given the ubiquity and accessibility of music in this age. Software designers creating gamified learning experiences can consider these findings when incorporating or designing music for specific levels and contexts

On the point of extraversion, it does appear that altering BGM tempo may instead be more effective for solo gamified learning experiences, since catering to a large group with varying extraversion levels is difficult. This may be true in cases where the goal is to maximise performance and thus, everyone will choose their preferred tempo. Indeed, this could be extended beyond gamified experiences and just solo learning and studying instead. However, BGM tempo can still play a role in situations where to goal is not to optimise performance, but to induce certain states. Dynamic tempo adjustments could cater to different contexts, such as a faster tempo to induce more engagement and stress in learners during a competitive activity, and a slower tempo to calm them down. Thus, whether in an individual setting or in a classroom, BGM could still be incorporated into gamified learning experiences either way.

Limitations and Further Research

While this experiment has presented some findings, there may be some limitations due to issues of generalisability. First, the experiment did not control for various variables, such as genre preference, music familiarity, music expertise, familiarity with data analysis software, or technology aptitude. Thus, the data may have some confounding factors which have not been uncovered. That said, this provides the groundwork for future research, such that the same experiment could be adopted while considering one of these variables as a covariate or a basis for a between-subjects experimental design, thus providing further insights into the current findings.

Furthermore, there was also a sampling bias due to the use of Panel HEC and word-of-mouth tactics, thus geographically limiting the recruitment pool to Montréal and largely students. Thus, it follows that further research could replicate this experiment with participants from other musical cultures, as they may interpret a certain tempo differently from the current sample. In recognising other musical cultures aside from the Western tradition, instrumental classical music from other musical traditions such as from Chinese classical music or Indian classical music could also be used with their associated cultural groups, or even cross-tested back with participants associated with the Western musical tradition. Other genres of instrumental music could also be used, such as jazz and soundtracks. Of course, other musical features could be varied as well, such as modality, volume, complexity, and even combinations of them. With music, there are infinite permutations to be tested here, especially when considering other musical traditions and their take on various musical features.

Lastly, the realism of the experiment was also limited by the laboratory setting and lack of social interaction unlike in a classroom or online platform. Replicating the experiment in groups, whether by groupwork or still solo experiences, could change up the dynamics by bringing in elements of social facilitation and competition. This would also enable to use of leaderboards with real-time updates to provide realistic game design elements as part of the experiment.

2.7 Conclusion

The experiment sought to answer two research questions: (**RQ1**) does BGM tempo affect a learner's performance in a gamified STEM learning context through the mechanisms of arousal and valence, and (**RQ2)** does extraversion moderate this relationship between background music tempo and learner's performance in a gamified STEM learning context. For **RQ1**, the findings suggest that BGM tempo does affect arousal, which then affects task performance in the context of the study. However, this was not shown to be the case for valence. Furthermore, for **RQ2**, extraversion was found to moderate this arousal-performance relationship. These findings generally corroborate the literature on tempo in the AMH framework, such that the arousal route is significant. It also confirms a Yerkes-Dodson relationship between arousal and task performance, such that a peak performance comes at an intermediate level of arousal. For the valence route's findings, this study adds to the side of the conflicting literature finding no interaction between tempo and valence, thus helping to clarify this relationship in future research. The experiment also highlighted the importance of having both physiological and self-reported measures of the same construct, as they may diverge and provide deeper insights into the results. In terms of the data analysis, it was seen that while p-values may be indicative of statistical significance, the effect sizes of the findings are equally important in identifying the practical significance and thus, the weight given to them. While detailing the findings, this article then ends by acknowledging the limitations of the experiment and suggesting avenues of further research, thus providing a blueprint for future experiments to build upon.

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Chapter 3
Sound Strategies: Using Background Music Tempo to Enhance Learning Experiences[2]

3.1 Introduction

Be it in traditional classrooms or technology-assisted settings, keeping students motivated and connected to the learning experience is essential for academic success. One way to achieve this is through gamification, which is the use of game design elements in non-gaming contexts. Commonly used game design elements like points, badges, and leaderboards are used to enhance motivation and engagement in students. However, music, which is a key component often present in games, has been underexplored in its potential for improving learning experiences.

In games, music shapes the atmosphere, influences emotions, and can even improve performance. Out of gaming, listening to your favourite music reduces stress (Jiang et al., 2013), playing music to foetuses stimulates neural development (López-Teijón et al., 2015), and listening to it while studying even enhances memory (Goltz & Sadakata, 2021). Despite these benefits, music as a tool in technology-mediated learning remains understudied. Combined with gamification, music could become a powerful supplement to enhance learning experiences, especially given its accessibility through the Internet. Its diversity also makes it adaptable and inclusive by catering to varied personalities.

[2] This article is in preparation for submission to a journal which is to be confirmed.

3.2 The Study

To explore the impact of music on learning, we pose two questions: (1) Does BGM tempo affect task performance in a gamified learning environment, and if so, (2) how does personality, specifically extraversion, influence this relationship?

We conducted a laboratory experiment involving 59 participants. For the musical manipulation, classical instrumental music is used for its lack of distracting lyrics, and tempo is the manipulated feature due to its ease of perception and classical music having a wide range of tempo. Since personality traits can shape how individuals perceive music, extraversion was included to the analysis to add depth. Each participant used a gamified platform that teaches data visualisation skills through six tasks. Each task had a multiple-choice question, and participants generated graphs to answer them. During the tasks, participants were exposed to three musical conditions: no music (control), slow music (<72 beats per minute), and fast music (>94 beats per minute). After every task, participants were told if they answered the question correctly and showed points and a simulated leaderboard. During the experiment, we also recorded both physiological and self-reported measures of arousal and valence, each corresponding to emotional intensity and emotional positivity or negativity respectively. Task success rates were noted manually, and participants completed a post-test questionnaire to report extraversion.

We found that faster music increases arousal, while slower music decreases it. Arousal positively impacts performance up to an optimal point, beyond which excessive arousal hinders it instead. This optimal point varies by extraversion, with extraverts tolerating higher arousal levels before performance worsens. Introverts, while more prone to overstimulation, perform better at baseline arousal. Though valence was examined, music does not appear to influence it. Notably, self-reported measures show greater statistical significance than physiological measures, suggesting that music affects the listener's perception of their emotions, even over their reflexive physiological responses. This suggests that BGM tempo can modulate arousal to align learners with situational needs, making it a powerful tool in education. Considering these results, we will next discuss how background music can be incorporated into learning experiences and even combined with gamification to further engage learners.

3.3 Recommendations

For educators

For teachers, a typical learning setting involves managing a classroom of students. This makes using BGM of one tempo difficult due to differences in personality. Instead, BGM tempo can be used like how it is in games: to create a specific atmosphere. For example, fast music could increase arousal in students, helping to create an energetic or stressful environment. This approach would not be to optimise performance but rather to intentionally vary the learning atmosphere. This can be particularly effective in competitive settings involving points and leaderboards. In contrast, slower music could help calm students and provide a relaxed atmosphere after an exciting activity.

If resources allow, performance optimisation can still be achieved by providing students with headphones or encouraging them to use their own. They could listen to a curated classical instrumental playlist at their preferred tempo to optimise learning. If the task is not complex, they could even listen to their preferred music as it has been shown to improve cognitive performance (Goltz & Sadakata, 2021). However, since headphones isolate students sonically, this approach is best used for activities with minimal interaction such as guided individual study sessions, where students work on assignments with a teacher available for help.

For software designers

For software designers creating gamified learning experiences, learners could be learning alone or in groups. If learning alone, BGM tempo can be optimised for performance. Giving learners the choice to choose their preferred BGM from a curated playlist can make BGM's inclusion much simpler and quicker. Clear categories, such as "slow" or "fast" or even "calming" or "stimulating" can make the selection more intuitive. Designers can also further enhance the experience by including a short survey to determine the learner's extraversion, then curate a playlist based on their answers. That said, learners should also be given an option to work in silence, as some individuals may find any music too distracting (Cassidy & MacDonald, 2007). Like in the classroom, BGM tempo can also be used to create atmosphere and influence emotions, even in individual settings. For example, a timed quiz could have the BGM tempo increase as the countdown approaches the end, creating urgency and pressure. This can be effective if used with points and leaderboards by upping the stakes. By creating a more competitive setting, the social dimension of gamification is also enhanced, (Zainuddin et al., 2020), thus increasing learner engagement as well.

For individual learners

Individuals have much more freedom in choosing music based on their needs and what they perceive to be "slow" or "fast". BGM tempo should be varied to fit a given task. For tasks requiring focus like reading or learning complex material, slow music helps provide stimulation without causing overstimulation. For high-pressure or creative tasks like brainstorming and timed activities, faster music could boost energy and focus. Streaming platforms like Spotify and YouTube offer a variety of curated playlists specifically for studying, such as classical, jazz, or lo-fi beats. By experimenting with different tempo for various tasks and considering one's extraversion, learners can identify playlists that best suit their needs. Personalisation can go even further by creating custom playlists tailored to specific needs, allowing learners to quickly tune in to specific situations.

3.4 Conclusion

Incorporating BGM into learning experiences offers a novel and accessible way to enhance engagement and optimise performance. It can also be used with gamification techniques to shape the atmosphere of the learning experience. By also understanding the relevance of personality traits like extraversion, educators and designers can tailor learning environments to suit the needs of diverse learners. For educators, this could mean using music to set the classroom atmosphere during group activities or providing individualised playlists in solo study settings. Designers, faced with typically solo learning experiences, could integrate BGM options into their platforms to make it easier for the learner to choose their ideal BGM or to enhance any competitive aspect of a platform using gamified social elements such as leaderboards. Ultimately, BGM holds a lot of potential in transforming both traditional and digital learning settings, allowing for more dynamic and inclusive experiences when the needs of individual learners are considered.

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Chapter 4
Conclusion

This thesis started by exploring the intersection between gamification, STEM learning, music as a stimuli, and personality traits influencing perceptions of said stimuli. In doing so, two research questions were posed:

RQ1: Does music help improve a learner's performance in a gamified STEM learning context?

RQ2: Does extraversion moderate this relationship between music and learner's performance in a gamified STEM learning context?

A within-subjects experiment was done to answer these questions, with participants completing a gamified experience teaching data visualisation skills. The experiment and its findings were reported in Chapter 2 in the form of a scientific article. In doing so, the research questions were narrowed down to focus on the musical feature of tempo specifically, due to its accessibility and ease of perception for the layperson. The arousal-mood hypothesis was employed to examine the effect of tempo changes on arousal and valence, and their resulting changes in performance, helping to answer **RQ1**. Eysenck's theory of personality on extraversion was also considered to study whether extraversion moderates the relationship found in **RQ1**, thus answering **RQ2**.

The arousal hypotheses were generally supported, though largely only for self-reported measures. For example, changes in BGM tempo were found to significantly increase or decrease arousal. However, there was a split between the physiological and self-reported measures, such that fast music has a significant positive effect on physiological arousal, but slow music shows no significant effect. Conversely, slow music has a significant negative effect on self-reported arousal, but similarly, fast music shows no significant effect. This split between physiological and self-reported measures continues, such as a non-linear relationship being found between self-reported arousal and task performance, and extraversion being a moderator for specific relationship.

On the other hand, the valence hypotheses had much less support. Slow music was found to significantly decrease self-reported valence, though it is suggested that this warrants deeper investigation for reasons which will be discussed shortly. A highly significant relationship was also found between self-reported valence and task performance. However, this was interpreted as a recency bias due to participants self-reporting valence right after knowing if they succeeded or failed the task and after viewing the leaderboard.

The findings above generally corroborate with the literature, be it on arousal or valence. For arousal, this comes in two prongs. First, the findings confirm the relationship between music tempo and arousal within the AMH framework and matches previous literature. Second, they showed an inverse non-linear relationship between arousal and task performance as described by the Yerkes-Dodson law and demonstrated the relevance of extraversion as a moderator in this relationship as predicted by Eysenck's theory of personality. While the valence hypotheses had less support, these findings help add weight to the side of the literature holding that tempo has no effect on valence.

For this thesis' methodological contributions, it was shown that employing both physiological and self-reported measures can provide a richer interpretation of a phenomenon and pave the way for more avenues of research. As the supported hypotheses leaned heavily in favour of self-reported measures, it appears that music may have such a strong effect on one's self-perception that it is able to override the body's actual response which is typically beyond the participants' conscious control (Ciuk et al., 2015). That said, the temporal nature of physiological and self-reported measures is also important, since self-reported measures are post-task and thus, subject to other biases as was observed in the highly significant self-reported valence and task performance relationship. Thus, it must be noted that the two measures cannot always be equated even if measuring the same variable, and thus care must be taken in interpreting the results. This care extends further to the interpretation of statistically significant findings based on p-values. Despite the data analysis finding statistical significance, weight was also given to effect sizes in the discussion of the results, as effect sizes implicate the practical significance of the relationship. This is not to say that small effect sizes are undesirable. At best, they contribute to the literature and indicate an opportunity for further research with a sample, and at worst, the results should be interpreted with caution if they seem to be of minimal practical significance.

The thesis then presented some practical applications of the findings in Chapter 3 which contains a managerial article for educators and software designers looking to incorporate music into their learning experiences. The recommendations acknowledge the direct applications of the findings by suggesting the use of background music at specific tempo adapted to the learner to optimise their learning experience, mostly in the context of solo learning. However, the findings are also extended by suggesting a use case where performance is not intended to be optimised, but impaired instead by using fast tempo music to artificially induce stress, helping to create a competitive setting especially in gamified situations using points and leaderboards. Some design suggestions for software designers are also provided, such as ensuring a no-music option on gamified platforms, curating preset playlists categorised by their effects (i.e. calming or stimulating) for users, or even using a short survey to determine the user's extraversion and recommending a playlist based on that.

As with any study, this thesis and its findings has its constraints. During the data collection process, we encountered some equipment failure which led to ten fewer measures of physiological arousal than self-reported arousal. This may lead to less accurate comparisons between the significance of physiological and self-reported arousal measures. However, the failures were assumed to be random as they did not appear to be specific in time or by participant. Thus, in using an LMM as justified by the within-subject nature of the experiment and acknowledging the random nature of the equipment failure, the impact of the missing data should be reduced. That said, the estimates may inevitably be less precise. The data collected could also be confounded by other variables that we did not control for, such as music genre preference; familiarity with the gamified content, specifically with analytics software; and aptitude and comfort with learning new technologies. For example, participants who are more at ease with technology may pick up the platform quicker and succeed in the tasks. Thus, measuring task success by including a time limit may exclude participants who are just needed more time to come to terms with the software. On music preference, individuals who prefer or dislike the classical genre may respond differently to the manipulation used, which may have affected their performance as well. Lastly, extraversion was assessed using only the two self-reported questions from the BFI-10. While this was done due to time constraints and the BFI-10 has shown to be reliable in matching the full BFI on extraversion, it could lack the depth of a more comprehensive instrument.

Another limitation is the generalisability of the results. First, there is a sampling bias as the sample was recruited primarily through the panel at HEC Montréal and by word-of-mouth strategies. As such, there is a geographic and demographic bias, with individuals largely being based in Montréal. This means that there may be cultural and regional differences in musical cultures, limiting the generalisability of the results as different musical cultures may interpret the same piece of music differently (Trehub et al., 2015). Furthermore, on generalisability, while the laboratory setting is ideal for controlling the experimental process, it may not be the most realistic setting, where external distractions and other social dynamics may exist. For example, if other learners were around, a participant may feel more driven to perform better due to the social facilitation theory (Zajonc, 1965). We attempted to replicate this feeling by creating a leaderboard which simulated the participant's movement around the leaderboard, but there were inevitably instances where the movement did not match the participant's expected placement. This also likely affected the participant's morale if they did not move the way they expected, thus biasing valence reports. As with any observed experiment, the Hawthorne effect may be in place (Roethlisberger & Dickson, 2003), such that participants do not accurately report their arousal and valence levels. Though the Hawthorne effect has been debated in its magnitude and relevance (Levitt & List, 2011), it remains recognised as a factor in experimental research and thus, measures were taken to reduce this by standardising interactions and having the participant and moderator in different rooms. Finally, while the manipulation used only classical instrumental music as the genre to provide a controlled and consistent auditory experience, using only one genre may limit the generalisability of the findings to other music genres. Related to the point of not controlling for music preference, this may also further generalisability as certain participants would have completed the experiment with their preferred genre, while others did so with their most disliked genre, thus affecting their performance.

While these limitations highlight the limits of the study, they also provide insights into avenues of further research. The experiment could be replicated with various adjustments in terms of variables, the sample population, or the manipulation. First, confounding variables can be captured in pre-screening surveys or demographic questionnaires to allow for more control of the eventual analysis. Such variables would include those mentioned earlier such as genre preference, familiarity with the skill being taught in the gamified experience, or technology aptitude. Accounting for these variables could be done in two ways: retain the within-subject design and including these variables as covariates in the resulting statistical analysis or use a between-subjects design to compare specific variables, such as between classical music lovers and non-classical music lovers. Next, for the sample population, testing individuals from different musical cultures will be interesting to see if the findings on tempo changes in their effects. Again, there are two ways to do this: diversify the pool to include participants from various geographic and cultural backgrounds to counter potential biases in musical interpretation or replicate the experiment in different regions. The latter is likely more feasible and simpler, as the former might result in a prolonged recruitment process beyond typical resources. Lastly, the manipulation could be varied in terms of the genre used. While this study used instrumental classical music, other forms of instrumental music could be used as well, such as jazz, film soundtracks or mediation music. The manipulation could even be combined with the participants' music cultural background. More specifically, classical music defined in this study is that from Western musical tradition. However, by incorporating world musical traditions, one could possibly compare the difference between, for example, the use of Western classical music and Indian classical music on participants familiar with the classical Indian musical tradition.

Another possible area of further research would involve improving the realism of the experiment. As stated earlier, the controlled laboratory setting of the experiment is far-removed from real settings in a classroom or online learning platforms where there are social interactions. Thus, it may be interesting to investigate if the findings change if the study was done in group settings, be it simply solo experiences done in a group, or actual group learning environments requiring participants to work in a group. By bringing in social dynamics, whether simply from social presence or actual interaction, the experiment could be extended to study the effects of social facilitation or competition in a gamified learning setting, while still using music tempo as the manipulation. This may even allow for the testing of one of the practical applications suggested in Chapter 3, specifically the use of faster tempo music to create a sense of competition in the classroom. Such settings also allow the use of real leaderboards and other game design elements, helping to strengthen the element of gamification in the experiment and properly align the game design element with participants' expectations according to their performance. In doing so, the effect of different game design elements can be compared too.

In summary, this thesis has helped advanced our understanding of the intersection between gamification, STEM learning, music as a stimuli, and personality traits such as extraversion. This was done by detailing theoretical and methodological contributions, providing practical recommendations, acknowledging the limitations of the study, and proposing avenues for further research. In doing so, this thesis provides a basis for deeper investigation into how gamified learning experiences can be improved by music-based interventions and considering personality traits.

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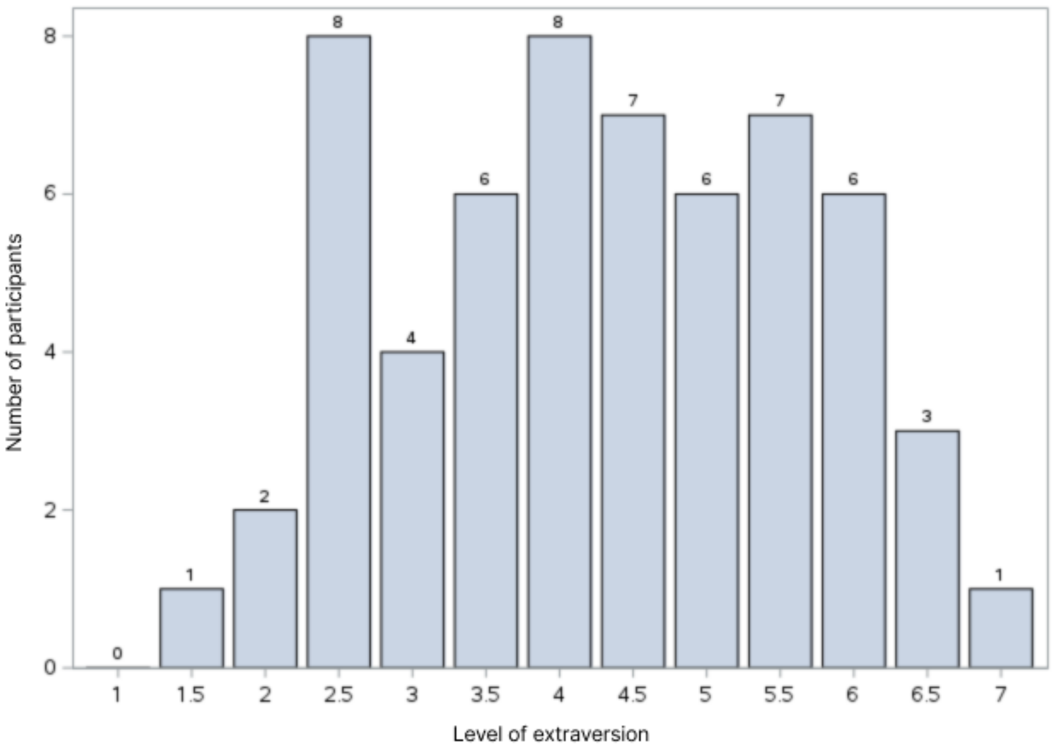
Appendices

Appendix A. Participant count across different levels of extraversion



Appendix B. Playlist for BGM tempo manipulation

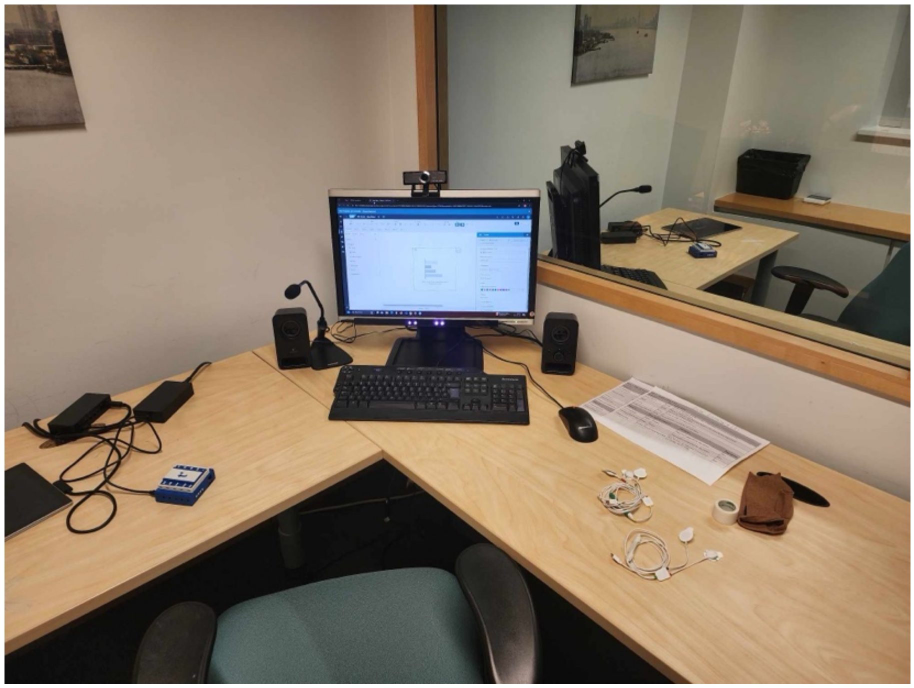
Slow music (<72 BPM)	Fast music (>94 BPM)
Chanson de Matin, Op. 15, No. 2 (Edward Elgar)	Suite No. 14 in G Major: VI. Gavotte (George Frideric Handel)
Den Blomstertid Nu Kommer (Israel Gustaf Kolmodin)	Ecossaise in E Flat Major (Ludwig van Beethoven)
Enigma Variations, Op 36: IX. Nimrod (Edward Elgar)	Le Lardon (Jean-Philippe Rameau)
Etude No 3 for String Quartet (Peter Sandberg)	Papageno Papagena (Wolfgang Amadeus Mozart)
Largo from Xerxes (George Frideric Handel)	Le Petit Rien (François Couperin)
String Quartet No. 19 in C Major, K. 465: I. Adagio Allegro (Wolfgang Amadeus Mozart)	Sonatina in G Major, Anh. 5 No. 1: I. Moderato (Ludwig van Beethoven)
	String Quartet No. 2 in D Major, K. 155: I. Allegro (Wolfgang Amadeus Mozart)
	String Quartet No. 12 in F Major, Op. 96, B 179, “American”: IV. Vivace (Antonín Dvořák)
	Suite No. 14 in G Major: VI. Gavotte (George Frideric Handel)

Appendix C. Participant and moderator set-up

The participant set-up consists of several components as seen in Figure C1. First, there is a monitor showing the Figma (Figma, Inc., 2024) mock-up and SAP Analytics Cloud (SAP SE, 2024) for the participant. Both stimuli were accessed with Google Chrome (Google LLC, 2024). Attached to the bottom of the monitor is a Tobii eye tracker (Tobii AB, 2024) and to the top is a webcam. A keyboard and mouse are also available for the participant for data input. Speakers are located on each side of the monitor from which the BGM tracks will be played. A data dictionary consisting of two sheets of paper with definitions of the variables used in the tasks is also within reach of the participant. There is also a microphone for the participant to speak to the moderator, a speaker under the table which allows the participant to hear the moderator, and a tablet on which the participant can read and sign the consent and compensation forms. The Bluebox (Courtemanche et al., 2018) is also located on the participant's end. The equipment consists of the Bluebox, a sync box from which it sends sync signals, and EKG and EDA sensors. Medical tape and gloves are also available to hold the sensors in place.

Figure C1

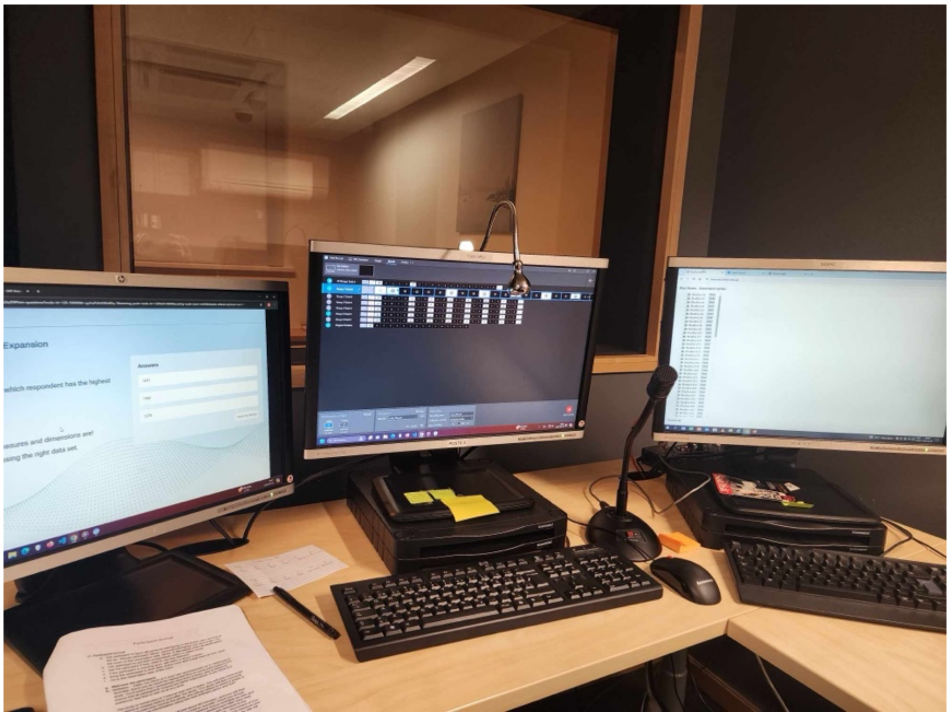
Experimental room



The moderator set-up consists of three monitors as seen in Figure C2. The left monitor mirrors the participant's monitor but also functions as an extended display of the middle monitor. The middle monitor runs Tobii Pro Lab (Tobii AB, 2024) for the eye tracking software and Windows Media Player (Microsoft Corporation, 2024) to play the music needed for the BGM tempo manipulation. The right monitor runs the Capture platform to allow the moderator to start and stop the webcam recording. Besides the monitors, the moderator also has a microphone to speak to the participant, a speaker to hear the participant, and a printed copy of the protocol at hand. A light is perched on the middle monitor to allow for easier reading of the protocol when the lights in the observation room are turned off.

Figure C2

Observation room



Though the experimental and observation rooms are separated by a wall, a hole in the wall allows for wired connections between the two sides. Thus, the right monitor in the observation room can run Capture to start and stop webcam recordings of the participant through a USB connection. To ensure synchronisation between the data recorded on the tools, two sources of timekeeping are used: sync numbers and NTP information over WiFi providing universal timestamps. The Bluebox and Capture first get timestamped with the NTP information. The Bluebox then sends sync numbers via Bluetooth to the sync box which is in turn connected via USB to the Tobii computer. These sync numbers are synced according to the timestamp identified by the Bluebox and are received as keyboard input on the Tobii Pro Lab.

Appendix D. Procedure

Participants were brought into the experimental room and left alone to read and sign a consent form. They were then asked several demographic questions, including age, sex, and gender. The moderator starts the webcam recording and enters the experimental room to install the EDA and EKG sensors on the participant for the Bluebox. The moderator then returns to the observation room to calibrate the Tobii eye tracker. After calibration, the participant accesses Qualtrics to answer a pre-test questionnaire which contains measures relevant to other manipulations in the experiment. Additionally, the participant was also informed of and asked to select the appropriate experimental group they were assigned to ensure that Qualtrics displays the right order of tasks. For the BGM manipulation, each participant was assigned to a group separately before the study which the moderator takes note of and manually selects the correct playlist.

The participant first views an introductory video and completes an introductory task to get acquainted with SAC. For the BGM tempo manipulation, participants are assigned to randomly ordered tempo conditions in pairs. As such, the first and second tasks, the third and fourth tasks, and the fifth and sixth tasks have the same condition each. The participant is given five minutes for each task. Music continues playing during the task and is stopped by the moderator before the participant answers the post-task questionnaire. Here, the participant will use the Affective Slider to self-report their arousal and valence. While the participant answers the post-task questionnaire, the moderator also records in the observation grid whether the participant succeeded or failed the task based on the graph produced.

After completing all six tasks, the participant completes a post-test questionnaire, including two extraversion questions from the BFI-10. A short post-test interview was conducted for the participant for comments on the music. The moderator then stopped all recording tools, both in the experiment room and observation room. Finally, the participant is given the tablet to complete the compensation form, then escorted out of the laboratory.

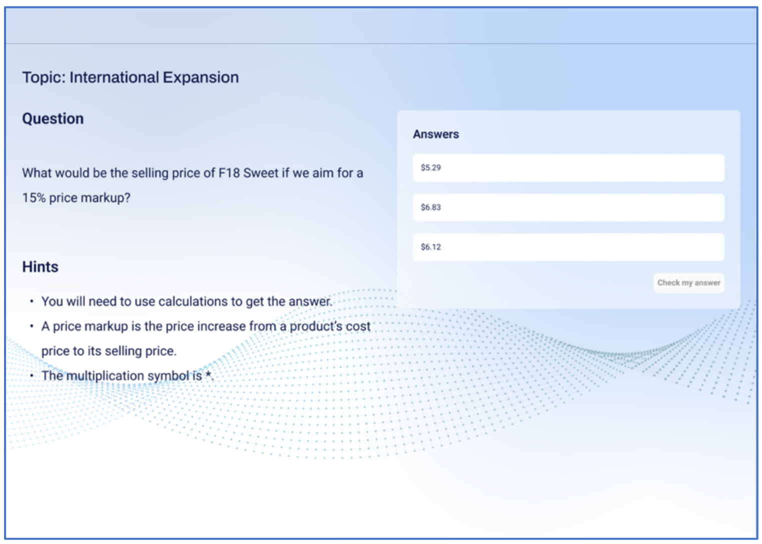
Appendix E. Figma mock-up flow and SAC set-up

Figma mock-up flow

The Figma (Figma, Inc., 2024) file is accessible via https://bit.ly/396tremblantfigma. The flow of each task is as follows:

Figure E1

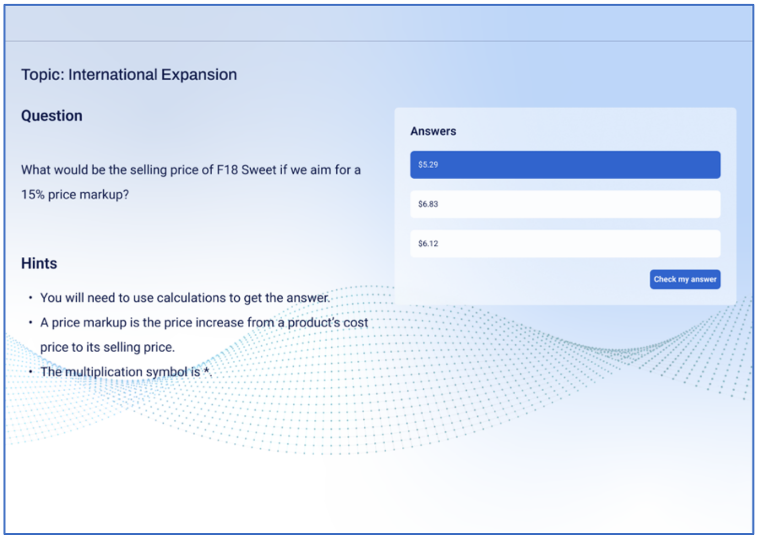
Step 1 of Figma mock-up – reading the question



The participant reads the question to be solved. To do so, the participant will have to generate graphs from curated datasets on another platform which will be discussed later.

Figure E2

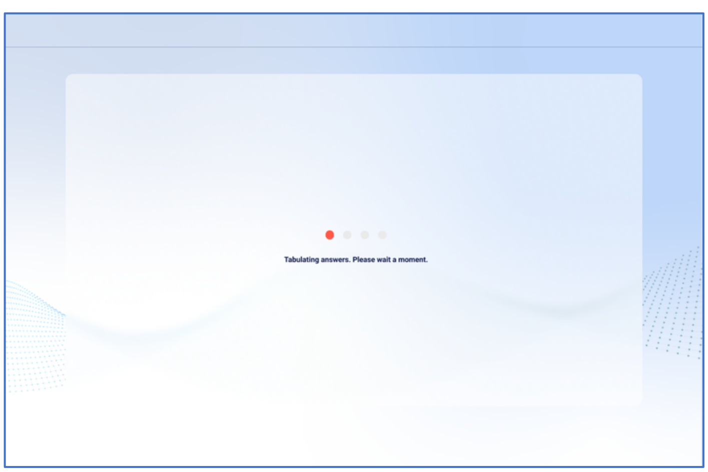
Step 2 of Figma mock-up – selecting the answer



The participant selects their answer based on the graph generated and clicks "Check my answer".

Figure E3

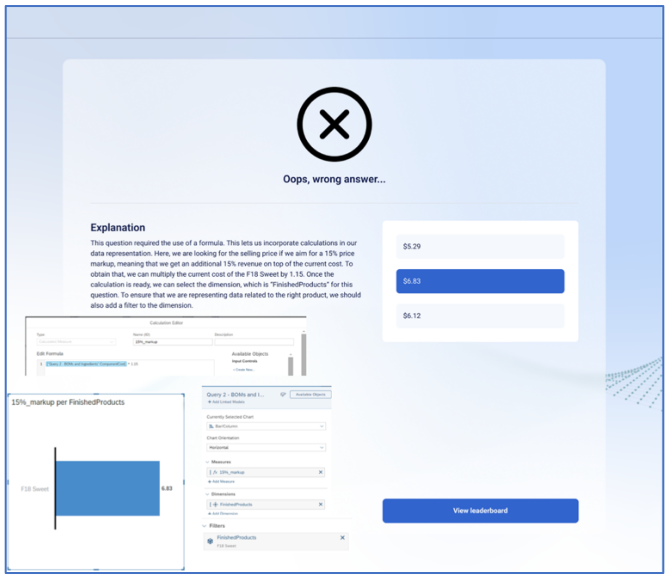
Step 3 of Figma mock-up – fake animated loading screen



A fake animated loading screen to transition into the next page was created to increase realism of the mock-up.

Figure E4

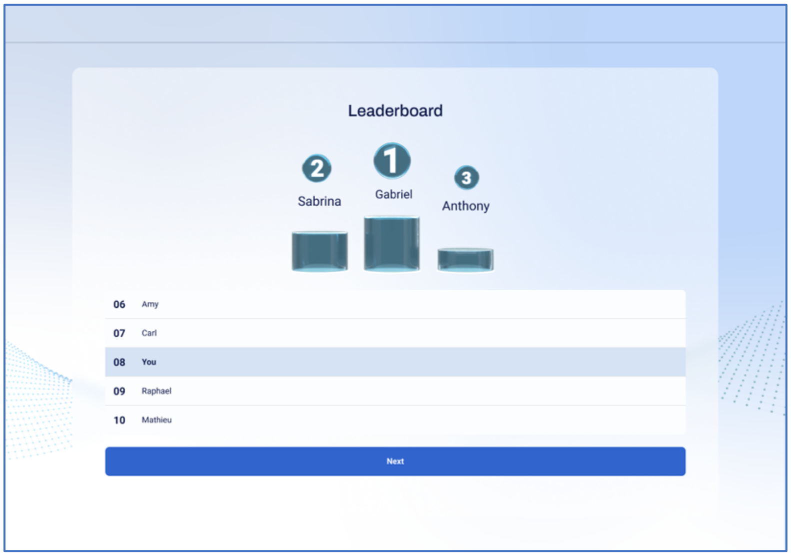
Step 4 of Figma mock-up – explanation page



The participant sees if they select the right answer. Regardless of whether they got it right or wrong, an explanation will be presented. The participant then clicks "View leaderboard".

Figure E5

Step 5 of Figma mock-up - fake leaderboard page



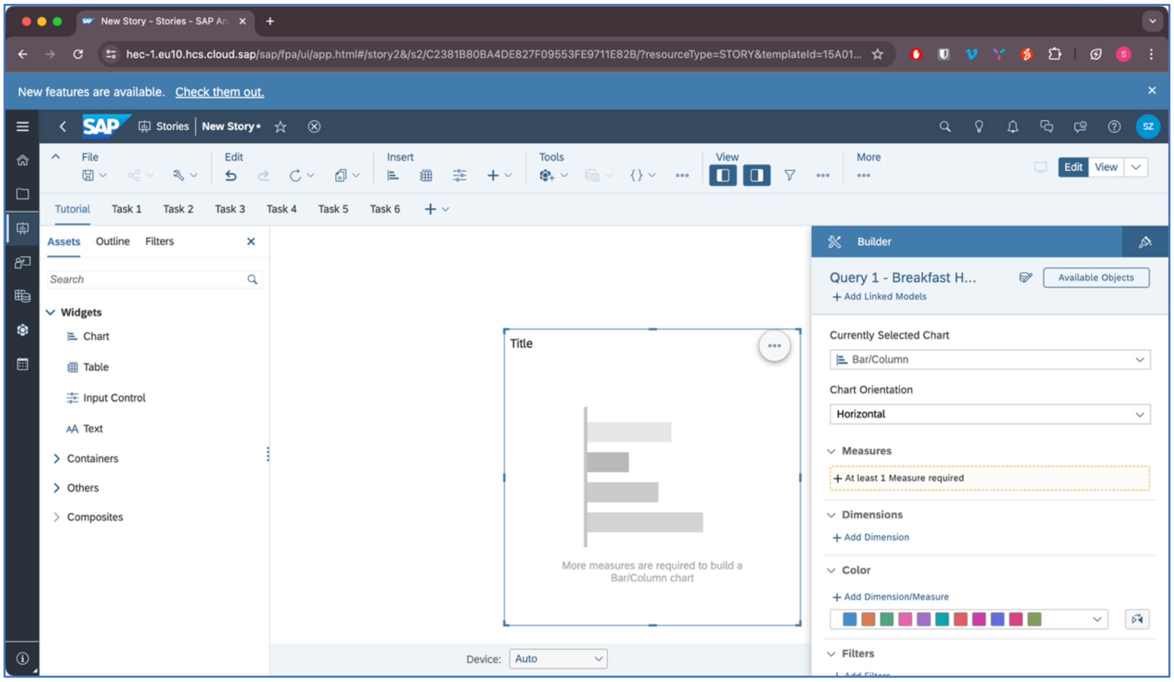
A fake leaderboard page was made which randomly moves participants up or down it after each task. The leaderboard was created to incite motivation, though it is not examined in this study.

<u>SAP Analytics Cloud (SAC)</u>

SAC can be accessed via https://bit.ly/396tremblantsac. Please reach out to the ERPsim Lab or email san-zhi.yap@hec.ca for access details. The platform stores the dataset from which participants can generate graphs and answer the questions found in the Figma mock-up. The dataset was created by the ERPsim Lab.

Figure E6

Screenshot of SAP Analytics Cloud



SAC is set up before the experiment to contain seven tabs in which the participant can work. The first is for the tutorial question while the remaining six are for the six questions they will complete over the six tasks.

Appendix F. Data mapping

Construct	Operationalised construct	Referenced construct	Comments
Arousal	*log_phasic*	Physiological arousal	Physiological, log transformed
	AS_Arousal	Self-reported arousal	Self-report
Valence	*Valence*	Physiological valence	Physiological
	AS_Valence	Self-reported valence	Self-report
Extraversion	*Extraver*	Extraversion	Self-report
Task Performance	*success_method*	Task Performance	Noted by moderator in observation grid