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Multitasking with Information Technologies: Why Not Just Relax?

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Abstract:

Multitasking with information technology (IT) may impact how much pleasure people experience during hedonic activities, especially multisensory activities that involve touching, listening, and watching. However, past research on IT multitasking has primarily focused on utilitarian professional contexts. Drawing from dual-task-interference theory and flow theory, we address this gap by hypothesizing how multisensory characteristics positively influence the hedonic experience and how that effect deteriorates with IT-related multitasking. In addition, we examine how personality traits influence this moderating effect. We conducted a mixed-method laboratory experiment using explicit (self-reported) and implicit measures (electrodermal activity, automatic facial analysis, and electroencephalogram) to test our hypotheses. Participants listened to music while sitting on a high-fidelity vibro-kinetic armchair (one that generates vibrations and movement perfectly aligned with the music) and engaged in simultaneous IT-related tasks. The results generally support our hypotheses and represent a call for people to mindfully avoid multitasking with their IT devices while enjoying hedonic activities. In addition, our results suggest that people high in extraversion or neuroticism personality traits are likely to be more vulnerable to IT-related deterioration effects in this context. This study contributes to explaining the multitasking phenomenon with IT during leisure activities and underlines the benefit of such activities' sensory characteristics.

Keywords: Multitasking, Hedonic Experience, Dual-task Interference, Vibro-kinetic, Multimethod, Electroencephalogram, EEG, Electrodermal Activity, Automatic Facial Analysis.

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1 Introduction

In this paper, we investigate the role that information technology (IT) can play in how much pleasure people experience during hedonic activities (especially multisensory activities that involve touching, listening, and watching) when using IT to multitask. Given that technology today offers relatively high accessibility, people (especially the younger generations, which many refer to as digital natives) have widely adopted mobile technologies (Prenski, 2001; Combes, 2006; Wright, 2001; Bennett & Maton, 2010). People use these technologies in many different contexts. For example, people commonly use their mobile devices while driving a car, walking on the street, listening to music, watching TV, or writing an email. Digital natives generally consider multitasking with IT a way of life and report finding it easy to do; they tend to believe that they are good at doing most normal activities while multitasking with IT, which includes actively communicating on digital social networks or watching movies on their mobile phones while doing their homework (Carrier, Cheever, Rosen, Benitez, & Chang, 2015). However, several studies have conveyed the idea that technology-related multitasking has an adverse effect on individual performance and attention (Gazzaley & Rosen, 2016; Strayer & Watson, 2016; Rosen, 2008; Bawden & Robinson, 2008; D'Arcy, Gupta, Tarafdar, & Turel, 2014) and suggested that the human brain can operate the most efficiently when a person performs a single task at a time as opposed to multiple tasks concurrently. Research has also examined conditions in which one might recommend IT-related multitasking (Cameron, Barki, Ortiz de Guinea, Coulon, & Moshki, 2018; Cameron & Webster, 2013; Stephens, 2012). We can find such a view in research on IT-enabled multicommunicating, which refers to individuals engaging in multiple (interleaved) communications with others in a period of time (Cameron & Webster, 2013). For example, Stephen (2012) asserts that one can desire IT-enabled multicommunicating for productivity, while Cameron et al. (2018) suggest that IT-enabled multicommunicating benefits individual performance more than face-to-face multicommunicating during team meetings. Likewise, Addas and Pinsonneault (2018) suggest that processing interrupting emails during productive business work can improve individual productivity if the emails agree with the primary task (and that they significantly harm individual productivity if they do not agree with the primary task). Furthermore, researchers have found multitasking to vary in impact according to some personality traits (Mark, Wang, & Niiya, 2014; Salomon, Ferraro, Petros, Bernhardt, & Rhyner, 2016; Küssner, 2017; Mesmer-Magnus, Viswesvaran, Bruk-Lee, Sanders, & Sinha, 2014). For instance, they have found multitasking to be associated with anxiety (Becker, Alzahabi, & Hopwood, 2018), an emotional state that is correlated with the two personality dimensions, neuroticism and extraversion (Gerber, Huber, Doherty, Dowling, & Ha, 2010; Leger, Charles, Turiano, & Almeida, 2016). Moreover, they have found multitasking to be associated with stress (Mark et al., 2014), a physiological state shown to be associated with personality during stimulating activities (Riedl, 2013).

However, research on IT-related multitasking has generally focused on professional or “functional” contexts in which individuals perform some productive tasks but with some simultaneous technology-related activities external to the main task (e.g., addressing pop-up emails while working on a central added-value task (Addas & Pinsonneault, 2018)). Despite important research efforts into examining multitasking, we know little about the role that IT-related multitasking may play in hedonic activities (i.e., activities that focus on enjoyment and pleasure (leisure activities)). An interesting topic would involve examining how IT-related multitasking may influence individual engagement in such activities. In our study, we contribute by empirically examining this question with respect to passive multisensory hedonic activities (i.e., activities in which participants have a passive (as opposed to active) role and in which their pleasure spawns from and is communicated through different senses (e.g., the user not only may touch or taste an object of leisure but also can feel the object's actions and reactions). Specifically, we examine the following research questions (RQ).

RQ1: To what extent does IT-related multitasking influence hedonic experience?

RQ2: Does this effect vary according to individual traits such as personality?

This paper proceeds as follows: In Section 2, we present the study's theoretical foundation and develop our hypotheses based on that foundation. In Section 3, we present the methodology we used to test our research model. We conducted a multi-method experiment (self-reported measures, electrodermal activity, automatic facial analysis, and electroencephalogram (EEG)) in which participants listened to music on a high-fidelity vibro-kinetic chair while multitasking using a mobile phone. We used neurophysiological measures along with self-reported measures to capture the effects during and after the hedonic task. In Section 4, we present the data analysis techniques we used, followed by the different results of the present study. Results generally suggest a detrimental effect of IT-related multitasking, which is more important for

people high in extraversion or neuroticism personality traits. In Section 5, we discuss the study's main findings along with its limitations and main contributions. Finally, in Section 6, we conclude the paper.

2 Theoretical Development

2.1 Dual-task Interference Theory

Researchers have used dual-task interference theory to explain the decrease in individual performance in multitasking settings (e.g., Pashler, 1994; Jenkins, Anderson, Vance, Kirwan, & Eargle, 2016). Dual-task interference refers to interference that occurs when an individual attempts to perform or attend to two tasks simultaneously (Pashler, 1994). The literature on multitasking uses two main theoretical perspectives to discuss dual-task interference theory: capacity sharing and cross talk. The divided attention paradigm—which posits that, when exposed to simultaneous stimuli (such as when executing simultaneous tasks), individuals switch attention between the stimuli—constitutes the foundation that these meta-models rest on. The capacity-sharing model suggests that, when attempting to complete or attend two tasks simultaneously, the human brain uses the same area for the two tasks, which compete for brain resources such as processing ability and speed (Pashler, 1994; Jenkins et al., 2016). Hence, as people have limited brain resources, processing performance deteriorates for each competing task (Marois & Ivanoff, 2005; Jenkins et al., 2016). The cross-talk model assumes that, if people perform two dissimilar tasks concurrently (such as texting on a mobile phone while driving), separate cognitive areas in the brain will activate and the communication between the two brain areas will conflict and ultimately make the brain confused (Pashler, 1994). This argument aligns with the bottleneck notion in task-switching (Jenkins et al., 2016; Ruthruff, Johnston, Van Selst, Whitsell, & Remington, 2003): if the foregoing brain areas require the same communication mechanisms or resources for task processing, one or both tasks will be delayed or impaired. We use the dual-task interference theory to develop our hypotheses.

2.2 Flow Theory

Csikszentmihályi (1988) developed the flow concept and characterized it as a mental state in which people who perform an activity engage in it to such a degree that nothing else seems to matter; this state can occur during not only physical activities but also interactions with logical systems such as mathematics and physical systems such as computers (Agarwal & Karahanna, 2000). Flow theory suggests that, as people get closer to the flow state, they get absorbed in the activity because they direct all their attention to it such that they have none left to allocate to other activities (Csikszentmihályi, 1988). Moreover, researchers consider flow an optimal experience and posited it to be associated with pleasure and enjoyment: the more people can experience flow, the higher quality of life they experience (Csikszentmihályi, 1990). Hence, with hedonic activities such as enjoying music while relaxing on a vibro-kinetic armchair, getting to the flow state should improve the hedonic experience.

2.3 Construct Conceptualization

2.3.1 IT-related Interaction

We situate the way we conceptualize IT-related interaction in the hedonic activity context. Admittedly, hedonic activities are very diverse and may include entertainment in several different settings such as board games, sport, cycling, relaxation, music listening or playing, or, interestingly, technology-based entertainment. However, IT-based entertainment generally requires several interactions with the technology; in this study, we distinguish between hedonic activities that feature IT-related interactions at their core (e.g., playing a mobile phone-based game) and hedonic activities that feature IT-related interactions outside the core activity (e.g., writing text messages (external) while watching a movie (core activity)). Hence, in IT-based entertainment, said IT would constitute the core stimulus and the “IT-related interaction” construct would refer to another separate technology that is not part of the core hedonic activity. For example, to illustrate IT-based entertainment, consider a situation in which an individual uses a social media platform on a smartphone for pleasure/enjoyment. In this case, the activities beyond that core hedonic activity constitute the IT-related interactions we care about (e.g., playing a chess game on the smartphone at the same time). In this study, we use the “IT-related interaction” or “IT interaction” constructs interchangeably to refer to the task(s) that an individual performs with technology as a separate and parallel operation to the central hedonic experience. As a result, we define IT interaction as whether an individual engages in parallel IT-based tasks while participating in a hedonic activity.

2.3.2 Multisensory Hedonic Experience

The term “hedonic” derives from the Greek term for “sweet”, which the Webster’s Ninth New Collegiate Dictionary defines as relating to or characterized by pleasure (Higgins, 2006). Hence, hedonic experience relates to feelings of pleasure and materializes via individuals’ emotional responses that spawn from their exposure to stimuli during a hedonic activity. One can find two main epistemological postures in the literature about emotions: the categorial perspective and the dimensional perspective. The categorial approach labels emotions into specific discrete categories (Grimm & Kroschel, 2005). We can see this approach in Ekman’s representation in terms of basic visually recognizable emotions such as joy, surprise, fear, disgust, anger, and sadness (Ekman & Friesen, 1978). However, this approach has a major limitation: human emotions constitute a large and continuous spectrum such that one may require too many categories or emotion categories may not be specific enough (e.g., one may be joyful and surprised at the same time). On the other hand, the dimensional approach for understanding emotions assumes that emotional responses comprise three core dimensions: emotional valence (the degree of positive affect), emotional arousal (the degree of excitation), and dominance (the extent to which an individual has control over a situation) (Bradley & Lang, 1994; Bynion & Feldner, 2017). Past studies have investigated the relationship between emotional valence and emotional arousal and generally found a very weak association between these constructs (Kuppens, Tuerlinckx, Russell, & Barrett, 2013) and theorized them to be “dimensions that can differentially respond across time to emotion eliciting events” (Bynion & Feldner, 2017, p. 2). We adopt the dimensional approach in the present study because it views emotional responses based on clear, independent dimensions. However, since we examine passive hedonic activities in this study, we do not adopt the third emotional response dimension (i.e., dominance) because, in passive hedonic activities (such as relaxing on a vibro-kinetic chair), participants typically surrender themselves to the activity, which minimizes their need for control that the dominance dimension represents (Bradley & Lang, 1994).

Moreover, we focus on multisensory hedonic activities (i.e., hedonic activities in which participants engage multiple senses to benefit from stimuli). Individuals may experience such activities through various senses such as smelling, visual, auditory, tactile, haptic, or taste. Research shows that the multisensory factor in multisensory hedonic activities positively influences the extent to which users appreciate the experience (Fenko, Kersten, & Bialkova, 2016; Noesselt, Tyll, Boehler, Budinger, Heinze, & Driver, 2010; Santangelo, Ho, & Spence, 2008). In this context, we expect a better multisensory hedonic experience to be associated with higher emotional valence because such an experience focuses on generating pleasurable feelings in participants, which entails that they experience positive affect throughout it. Furthermore, we expect a better multisensory hedonic experience to be associated with higher relaxation and lower arousal (greater calm) in activities that focus on relaxing (and to lower relaxation and higher arousal—lower calm—in activities that focus on physiological excitement). In this paper, we focus on hedonic activities that focus on relaxing.

2.3.3 Personality Traits

As we mention in Section 1, past work has associated multitasking with personality (Mark et al., 2016; Salomon et al., 2016; Küssner, 2017; Mesmer-Magnus et al., 2014). As for why, some research has found multitasking to be associated with anxiety (Becker et al., 2018; Terry, Mishra, & Roseth, 2016) and stress (Mark et al., 2014), two emotional and physiological states whose manifestations vary with the personality trait, extraversion (Gerber et al., 2010; Leger et al., 2016; Riedl, 2013). Numerous studies have investigated personality dimensions in diverse contexts. In psychology, the five-factor model (FFM) suggests that five factors determine personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism (Paunonen & Jackson, 2000). Past research has found only extraversion and neuroticism among these five dimensions to be associated with anxiety (neuroticism positively and extraversion negatively) (Kaplan, Levinson, Rodebaugh, Menatti, & Weeks, 2015). Thus, given these findings and their apparent relevance to our study, we considered only the neuroticism and the extraversion dimensions to investigate the role that personality has on people’s experience during multitasking. Moreover, among the five personality dimensions, neuroticism and extraversion account for most of the variance in the personality domain (Iluguru, n.d.), which suggests that one would have a higher chance to identify significant impact from a small or medium sample size. A high level of positive emotionality, sociability, activity, and assertiveness characterizes extraversion (Gerber et al., 2010; Leger et al., 2016). It also includes “an energetic approach to the social and material world” (Gerber et al., 2010, p. 113). On the other hand, anxiety and depressive symptoms typically characterize neuroticism (Leger et al., 2016).

2.4 Hypothesis Development

2.4.1 Impact of the Multisensory Characteristic

Past studies suggest that a multisensory hedonic activity enhances hedonic experience more than a unisensory hedonic activity (e.g., Giroux et al., 2019; Pauna et al., 2018; Donley, Ritz, & Shujau, 2014; Santangelo et al., 2008; Moran, Molholm, Reilly, & Foxe, 2008). More specifically, Giroux et al. (2019) investigated the effect that high-fidelity vibro-kinetic chair movements had on people's emotional experience when they listened to music. They found that the chair's multisensory nature induced higher emotional valence compared to the unisensory condition (i.e., music listening in the same chair but without vibrations). Likewise, Pauna et al. (2018) conducted a study in which they placed participants in a cinematic experience while they sat on a vibro-kinetic chair and found that high-fidelity vibro-kinetic chair movements had a positive effect on emotional valence. Hence, in this perspective, we expect that a multisensory setting will induce greater emotional valence than a unisensory setting. Besides, studies have found relaxation to be associated with lower arousal (e.g., Sandler et al., 2017; Pelletier, 2004; Logan et al., 2001; McGlynn, Moore, Rose, & Lazarte, 1995). For example, Sandler et al. (2017) found relaxation to be associated with a decrease in electrodermal activity, a physiological indicator that researchers have extensively used as a measure for emotional arousal (Riedl & Léger, 2016). Moreover, based on conducting a meta-analysis on the effect that music has on emotional arousal, Pelletier (2004) found that music-assisted relaxation decreases emotional arousal. Hence, in our study, we expect that a multisensory setting will induce lower arousal than in a unisensory setting. Hence, we hypothesize:

H1a: A multisensory hedonic activity generates more positive emotional valence compared to a unisensory activity.

H1b: A multisensory hedonic activity generates lower emotional arousal compared to a unisensory activity.

2.4.2 Impact of IT-related Multitasking

As we mention in Section 1, IT-related multitasking has an adverse impact on attention and performance (Strayer & Watson, 2016; Gazzaley & Rosen, 2016; Rosen, 2008). When an individual engages in a relaxing multisensory hedonic activity, actively engaging in simultaneous IT-related tasks generates interruptions and attention switching (Gazzaley & Rosen, 2016). Thus, to perform IT tasks while benefitting from a hedonic activity, one would need to expend effort to switch one's attention. This logic concurs with the divided attention paradigm and the capacity-sharing model of dual-task interference (Pashler, 1994, Jenkins et al., 2016); the attention-switching results from the fact that multisensory stimuli would require common but limited cognitive resources. A degradation in individuals' attention leads to their engaging less in the core leisure activity and, thus, hampers the pleasure they experience. Moreover, based on the cross-talk model (Pashler, 1994), we can expect that, as IT-related parallel activities differ from multisensory activities, conflicting communication in the brain will occur because separate brain areas will likely activate to handle the concurrent activities. In turn, this conflicting communication will not only weaken how well individuals can cognitively process multisensory stimulations but also hinder their pleasure and enjoyment, and, thus, create a worse hedonic experience.

Flow theory provides further insights. Attaining the flow state (full absorption) in a multisensory hedonic activity requires a subject's complete attention, involves pleasure and enjoyment, and likely results in an optimal experience as per Csikszentmihályi (1990). Yet, engaging in parallel interactions with an IT during the hedonic activity would partly divert an individual's attention. Thus, such behavior would hamper the individual's ability to experience the pleasure and enjoyment that a relaxing multisensory hedonic activity induces. Based on this argument, we can logically argue that IT interactions will have an adverse effect on the emotional reaction that a multisensory hedonic experience induces. Accordingly, we hypothesize:

H2a: IT-related interaction negatively moderates the effect that a multisensory hedonic activity has on emotional valence.

H2b: IT-related interaction negatively moderates the effect that a multisensory hedonic activity has on emotional arousal.

Hence, we expect a lower emotional valence effect with parallel IT-related interaction than without IT-related interaction. We also expect greater induced emotional arousal with IT-related interaction than without IT-related interaction.

2.4.3 The Role of Personality

Several studies have suggested that people high in extraversion experience greater increases in positive affect in response to positive stimuli (Leger et al., 2016; Gomez, Cooper, & Gomez, 2000; Schneider, Rench, Lyons, & Riffle, 2012). On the other hand, some other studies show that people high in extraversion experience less decline in positive affect when dealing with negative events such as stress (Leger et al., 2016; Penley & Tomaka, 2002). For example, Küssner (2017) has suggested that extrovert people benefit more than introvert people from listening to background music while simultaneously conducting a cognitive task. Therefore, we can reasonably expect that operating technology during a multisensory hedonic activity will degrade the experience less significantly for people higher in extraversion. Accordingly, we hypothesize:

H3a: The higher an individual's extraversion, the weaker the negative moderation impact that IT-related interaction has on a multisensory hedonic activity's effect on emotional valence.

Moreover, past studies have found extraversion to be positively associated with stress (Swickert, Rosentreter, Hittner, & Mushrush, 2002; Loerbroks, Apfelbacher, Thayer, Debling, & Sturmer, 2009), a construct that they have operationalized as reflected by physiological activation (e.g., through higher cortisol levels); that is, emotional arousal (Loerbroks et al., 2009; Riedl, 2013). Hence, we can expect extraverts to exhibit higher physiological arousal when a stressor such as the need to interact with a mobile phone in a multitasking setting stimulates them (e.g., Schneider et al., 2012). Accordingly, we hypothesize:

H3b: The higher an individual's extraversion, the stronger the negative moderation impact that IT-related interaction has on a multisensory hedonic activity's effect on emotional arousal

On the other hand, past studies have found neuroticism to be positively associated with negative affect (Feng, DeMarco, Haroon, & Riling, 2015) and that people with higher neuroticism experience a more sensitive increase in negative affect in response to a stressor (Schneider et al., 2012). In this regard, people high in neuroticism tend to display hyper-reactivity to stimuli. In our study, because engaging in parallel IT interactions requires a certain degree of attention and cognitive effort, we consider such engaged technology use comparable to a stressor: it constitutes a constraint that an individual experiences in parallel with the core multisensory hedonic activity. Accordingly, we hypothesize:

H4a: The higher an individual's neuroticism, the stronger the negative moderation impact that IT-related interaction has on a multisensory hedonic activity's effect on emotional valence.

Moreover, research suggests that neuroticism is positively associated with stress (Mark et al., 2014). Hence, we can expect highly neurotic people to experience higher stress through higher physiological activation when exposed to a stimulus. Accordingly, we hypothesize:

H4b: The higher an individual's neuroticism, the stronger the negative moderation impact that IT interaction has on a multisensory hedonic activity's effect on emotional arousal.

Hence, we expect "moderated moderation" (Hayes, 2013, p. 331) relationships with extraversion and neuroticism factors as second-level moderators. We depict our research model in Figure 1.

3 Methodology

3.1 The Hedonic Setting

To test our multisensory experience model, we conducted a laboratory experiment that the ethics committee of the laboratory's university approved. The experiment typically involved participants multitasking using technology (a mobile phone) during a relaxing leisure activity. They listened to music as they sat comfortably on a high-fidelity vibro-kinetic (HFVK) armchair that D-BOX Technologies designed (Canada)¹. As such, the armchair could produce artistically developed vibrations and movements. The armchair perfectly synchronized its vibrations and/or movements with each song that participants listened to. Hence, while listening to the songs, they could feel smooth vibrations and movements. Other researchers have also used the HFVK armchair in many previous studies (e.g., Giroux et al., 2019; Pauna et al., 2018; Tchanou, Giroux, Léger, Senecal, & Ménard, 2018; Gardé et al., 2018a, 2018b).

¹ Please see Boulais, Lizotte, Trottier, and Gagnon (2011) and Roy, Bérubé, and Jacques (2003a, 2003b) for D-BOX Technologies patents.

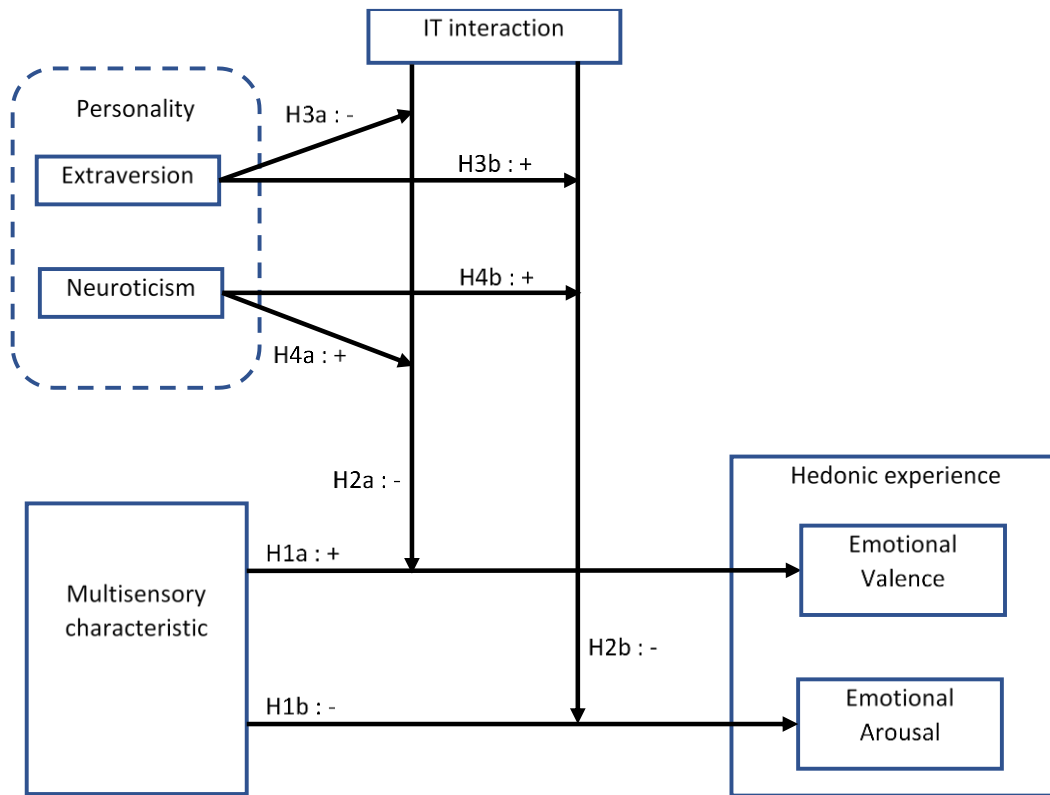


Figure 1. The Research Model

Participants experienced a multisensory music listening activity since they used multiple senses to enjoy the experience. While they listened to music while relaxing on the armchair, they performed an IT-related task on their smartphone as a peripheral activity. We played the songs through a 5.1 home cinema surround sound system to provide an immersive music listening experience. In the experimental room, we reproduced a living room ambiance by placing a small table and a floor lamp next to the chair. We illustrate the experimental setting in Figure 2.



Figure 2. The Experimental Setting

3.2 Participants

The community panel of the laboratory's institution served as the platform that we used to recruit a homogeneous participant sample. In particular, we targeted millennials since one can reasonably assume that they are digital natives (Prensky, 2001) and would showcase more typical IT-related multitasking during the experiment. To participate in the study, participants had to be 18-year old or older and needed advanced reading and listening skills. Also, the participants could not participate in the study if they had skin sensitivity or skin allergy, cardiac pacemaker, epilepsy, neurological diagnostics, or any other health-related diagnostics. In total, 24 participants participated in the study (54% females). Their median age was 22 (with a five-year standard deviation).

3.3 The Experiment

3.3.1 Experimental Stimulus

We had participants interact with IT as the IT-related activity interfered with their multisensory hedonic activity. They interacted with IT through a mobile application that we developed based on a Web-based architecture using the Axure RP 8 integrated development environment. Figure 3 showcases what the mobile application looked like. We made the application simulate a popular music listening mobile platform. For every song played during the experiment, we created a set of interfaces. To induce users to engage with the application, the interface provides information about the song that is being played. We wanted to make sure the participants actively interacted with each song's interface without any break and starting from when they began to when they ended listening to each song. For every song, we prepared six to ten pages that contained between 50 and 100 words about the song's miscellaneous properties according to its length (500 to 600 words in total for each song). This information included the song's artist, the album in which the song appeared, the song's lyrics, the video clip information, and other facts related to the song. In addition, we blended related pictures with text. Participants could easily navigate through the application (next page button click), and we restricted their ability to skip songs. By controlling the actions that participants could perform in the application rather than using a pre-existing application, we made sure they could easily use it and that they focused on the relevant tasks (i.e., looking up song information). Participants used the mobile application on a smartphone (an Apple's iPhone).



Figure 3. Example of Stimulus' Page (in French in the Experiment)

3.3.2 Experimental Protocol

After we welcomed participants and made sure they met the experiment requirements, we asked them to complete an initial questionnaire that measured their personality traits. Then, a research assistant installed and adjusted the measurement tools on the participants. After that, we invited them to sit in the HFVK chair and to adjust the chair's inclination so that their feet could not touch the ground. By doing so, we made sure that all the participants would feel the same floating effect from the HFVK chair, which offers the best experience when one cannot touch the ground. We also made sure that they did not incline the chair too much so that a camera could properly capture their facial expressions throughout the experiment.

Before the task, we explained to the participants that they would have to listen to different songs while sitting in the chair while interacting or not with a smartphone. We played the first song in the control condition in which the HFVK chair did not move and they listened to a song without any interaction with the mobile application. Before participants listened to each song, we told them whether they had to simultaneously engage in using the mobile application. If they had to do so, we asked them to start consulting the information immediately when they heard the song start to play. We also asked them to keep the mobile device in a position so that it did not hide their face from the fixed camera recording. In all cases, we asked them to keep their eyes open for each song's full duration. When the participants did not have to interact with the mobile application, we asked them to simply listen to the song playing.

After participants listened to each song, we had them fill out a short 15-item questionnaire that assessed the different emotions they experienced during the task. In total, we played 15 songs that individually lasted between 136 and 193 seconds (mean: approximately 162.5 seconds, SD: 18.3 seconds). At the end of the experiment, we conducted a short interview (about five minutes) with each participant before giving them a \$40 gift card (in CAD) as their compensation for participating in the experiment. We administered all questionnaires through Qualtrics.com, an online survey platform, on a tablet PC.

3.3.3 Experimental Design

We used a 2 x 2 within-subject experimental design. The first factor represents a hedonic activity's "multisensory" nature: whether the armchair generated vibro-kinetic movements that perfectly synchronized with the songs or did not generate any movement at all depending on the condition. The second factor represents IT-related interaction: whether participants actively interacted or did not interact with the smartphone application when listening to music. The no-movement, no-IT condition served as the control condition. We show the treatment conditions in Table 1 and use the naming scheme in the table in the following sections.

Table 1. Experimental Conditions

	With IT	No IT
With HFVKM	M_IT	M_NoIT
No HFVKM	NoM_IT	Control

To further improve the experiment's internal validity, we controlled for two variables: participants' previous experience with the song (how frequently the participant had listened to each song) and how much they appreciated each song. We used these two variables as controls due to the likelihood that participants already knew and had listened to the songs we played. Moreover, we required all participants to keep their eyes open when listening to the songs except for normal and spontaneous eye blinks. We base the rationale for this experimental control in the literature about EEG, which suggests that closing one's eyes when resting increases brain alpha waves and, thus, induces a higher relaxation state (Müller-Putz, Riedl, & Wriessnegger, 2015). Hence, we needed to ensure all participants kept their eyes open to dismiss eye-opening status as a confounding factor. Furthermore, we had to make sure to set the light level in the experimental room at an appropriate level since lighting can potentially generate artefacts (noise signals) in EEG signals. Hence, we exposed all participants to the same lighting level (i.e., low and filtered lighting).

We chose 15 songs in total and, for each participant, randomly assigned each song to exactly one of the four treatment conditions. This randomization helped mitigate possible error terms due to song choice. Moreover, the songs were played in a random order for each participant. This temporal ordering of the experimental conditions helped minimize possible carryover effects and constitutes a recommended best practice in the literature (Keppel & Wickens, 2004).

Moreover, to reduce human error-related noise that could be associated with manually playing the playlists, we automated the playlist for each participant using Python: for every participant's playlist, we developed one Python program, which led to 24 playlist programs in total. Hence, the playlists operated semi-automatically with minimal human intervention. In automating the playlists in this way, we helped reduce possible human errors due to manually manipulating the vibro-kinetic armchair's digital files related to the songs; besides, it automatically handled complex and long manual Microsoft Windows commands that we needed to use to run every song in a mode that the vibro-kinetic armchair controlled.

3.4 Measures

We conducted our study using a multi-method approach. Self-reported questionnaires (explicit measures) served as measurement instruments in addition to neurophysiological measurement instruments (for implicit measures). Unlike perceptual explicit measures that capture only how participants remember their experience *ex post*, neurophysiological indicators can capture participants' real-time experience during and after an experimental task.

3.4.1 Explicit Measures

Researchers have referred to self-reported measures as explicit measures because they capture perceptual factors that individuals report as per their awareness of the factors' levels (Ortiz De Guinea, Titah, & Léger, 2014). We used a questionnaire to assess participant's emotional arousal (four items, adopted from Ortiz de Guinea et al. (2013)), emotional valence (three items—new scale), previous exposure to the listened song (i.e., how frequently a participant had been exposed to the song), and appreciation of the song (i.e., the extent to which a participant likes the song), all with a seven-point Likert scale. We included six other irrelevant items in the questionnaire to psychologically and methodologically separate the constructs' items (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) and, thus, mitigate possible common-method bias from participants' habituation (decreased conscious response) due to repeated exposure to the same items (Anderson, Jenkins, Vance, Kirwan, & Eargle, 2016). These extra items measured three emotions that participants experienced during the task: sadness (two items that we adopted from Stuijzand et al., 2016), boredom (three items that we adopted from van Tilburg & Igou, 2012), and anger (one item that we adopted from Juslin, 2000)).

We developed and validated the above emotional valence scale to fit the study's context. To assess content validity, we followed a Q-sorting approach (Moore & Benbasat, 1991). We wrote each question on separate cards and asked three Ph.D. students to match each question to one of three constructs (emotional valence, emotional arousal, and cognitive load). We then calculated their inter-rater agreement (Cohen's kappa of 0.735). The literature suggests (Moore & Benbasat, 1991) Cohen's kappa scores greater than 0.65 as acceptable. Thus, we found support for our valence construct's content validity. Moreover, to assess the reliability of the emotional arousal and the emotional valence measures, we administered the emotional arousal and emotional valence questionnaire in a pre-test in which 22 participants used a website and provided feedback about their user experience. Based on the collected pre-test data, we assessed the two measures' reliability. We obtained a Cronbach's alpha of 0.736 for emotional arousal and a Cronbach's alpha of 0.510 for emotional valence. We then had an expert in linguistics check the items. Based on his advice, we slightly reworded one item of emotional valence that correlated the least with the other items. We also added two high-loading items from Deng and Poole (2010) (composite reliability of 0.92) to the emotional arousal measure to replace one item that participants found confusing. Subsequently, we conducted another pre-test during which four participants listened to three songs each in the multisensory condition on the HFVK armchair. Thus, this second pre-test provided a total sample of 12 answers to the questionnaire. A new reliability assessment yielded a Cronbach's alpha of 0.879 for emotional arousal and 0.723 for emotional valence. Research suggests that Cronbach's alpha values must be greater than 0.60 for one to consider them good early in a study (Moore & Benbasat, 1991). Hence, the constructs had satisfactory reliability. To further confirm the reliability of our emotional arousal and emotional valence explicit measures, we did a post hoc reliability assessment after we completed the experiment. We achieved a Cronbach's alpha of 0.875 for emotional arousal and a Cronbach's alpha of 0.793 for emotional valence, which further strengthens their reliability. We administered the questionnaire for arousal and valence right after participants listened to a song.

To measure our participants' personality traits, we used the 24-item Eysenck personality questionnaire (Francis, Brown, & Philipchalk, 1992) with a five-point Likert scale. The questionnaire measures two independent personality dimensions, extroversion and neuroticism, which account for most of the variance

in the personality domain (Iluguru, n.d.). We administered this questionnaire before starting the experimental tasks.

At the end of the experiment, we conducted a five-minute semi-structured interview with participants to learn about their impressions on their multi-sensory hedonic experience and to learn about their willingness to live it again. First, we asked whether participants would have preferred closing their eyes throughout the activity. Second, we asked whether they would like to live the experience again. Finally, we asked for general comments in an open-ended style (see Appendix A). The first two questions required a “yes” or “no” answer, but we allowed participants to freely explain their answers and provide a rationale for them. We summarize the explicit measures in Appendix A.

3.4.2 Implicit Measures

IS researchers have widely used explicit (self-reported) measures as they offer several advantages. For instance, they allow one to collect data relatively easily and rigorously validate content since one can broaden or narrow their focus as needed (Tams, Hill, Guinea, Thatcher, & Grover, 2014). However, explicit measures do have some limitations. For example, they are prone to social desirability and common method bias. Furthermore, they capture only conscious perceptions and thoughts outside (e.g., before or after) task occurrence (Riedl & Léger, 2016). On the other hand, implicit measures complement explicit measures in the sense that they can capture automatic, unconscious states and explain additional variance in dependent variables during the experience. Moreover, they can often report factors’ real-time states. Furthermore, social desirability bias does not affect them and they reduce common-method bias since they do not rely on a single measurement method (Dimoka et al., 2012; Tams et al., 2014; Riedl & Léger, 2016). In this study, we triangulated the explicit measures of emotional arousal and emotional valence with implicit measures (i.e., neurophysiological measures). Specifically, we used three such measures: electrodermal activity (EDA), automatic facial analysis, and electroencephalography.

One can measure EDA, also called galvanic skin response or skin conductance, using a galvanometer—technology that allows researchers to capture skin conductance in reaction to a stimulus. Using two electrodes (one anode and one cathode), it measures the degree to which the skin permits an applied electrical current to transmit through it based on the state of sweat glands (i.e., it measures the skin’s electrical conductivity) (Riedl & Léger, 2016). The EDA indicates autonomic nervous system arousal in response to a stimulus in an objective, transient manner (Lempert & Phelps, 2014). One can also use it to measure people’s emotional arousal states as they engage in activities (Dimoka et al., 2012). We used EDA in our study for emotional arousal. We placed electrodes on the participants’ hands to measure their EDA. We used the EDA signal amplitude to measure arousal for our experiment’s different trials. We used the software Acqknowledge (which Biopac Systems develops) to record and analyze EDA that we captured via the sensors on participants’ hands. We adjusted the EDA value for a baseline value, which we captured before each trial, and used the raw differences for analyses.

Moreover, we used an implicit measure of emotional valence that we generated through automatic facial analysis. Based on work that Ekman and Friesen (1978) pioneered, one can generally link human emotions to specific sets of facial muscle contractions. These muscle contractions constitute muscle actions called action units (AU), and humans can produce a very large set of AUs (Martinez, Valstar, Jiang, & Pantic, 2017; Srinivasan, Golomb, & Martinez, 2016). Automatic facial analysis (AFA) refers to a method that uses sophisticated algorithms such as 3D modeling and machine learning to identify and interpret AU sets to map them to specific emotions. The AFA method allows one to quickly analyze huge volumes of video data to detect facial expressions, which one would find difficult or impossible manually (Lewinski, Fransen, & Tan, 2014). In particular, we relied on the software program FaceReader (that Noldus Information Technology produces) to conduct the video-based facial analysis based on the AFA method. FaceReader can detect up to seven positive, negative, or neutral emotional states from micro facial expressions (categorical approach for measuring emotions) and generates emotional valence (dimensional approach) from that data. This non-invasive (no physical lesion required) method measures the positive or negative valence that participants express via their facial emotions in real-time. We used a fixed camera to record each participant’s face during the experiment. We used the software program Media Recorder (which Noldus Information Technology develops) to record the video and audio, which we then analyzed using FaceReader.

Finally, we used brain waves to measure the relaxation states of participants during the experimental tasks. We captured brain waves using an electroencephalogram (EEG), a non-invasive neurophysiological tool that records neuron electrical activity in the cerebral cortex with high temporal precision (i.e., in milliseconds) (Riedl & Léger, 2016). An EEG device comprises a set of electrodes that capture brain electrical signals.

One places these electrodes at specific locations on the scalp to pick up and map brain waves in different brain regions (Riedl & Léger, 2016). To collect EEG data, we replicated EEG settings that Pauna et al. (2018) applied in also studying HFVK effects using the D-Box armchair. Our EEG device comprised 32 BrainVision electrodes (Brain Products GmbH, Munich, Germany) and an Easycap helmet (Easycap GmbH, Munich, Germany). EEG data represents brain waves as frequency bands. In the literature, EEG frequency bands have names, such as delta, theta, alpha, beta, and gamma waves. Researchers have found these frequency bands to be associated with several physiological states. Because we care about participants' relaxation, the alpha frequency band pertains to the present study as researchers have found it to be positively associated with relaxation states while awake (Müller-Putz et al., 2015); that is, the more alpha, the more relaxed one can expect a participant to be. Moreover, researchers have associated the alpha band with skin conductance levels to assess individuals' physiological arousal (Barry & De Blasio, 2018). A medium-frequency range (8 to 13 Hz) and an amplitude that typically ranges 20 to 200 μ V characterizes the alpha waves (Müller-Putz et al., 2015).

We used the software program Observer XT (Noldus, Wageningen, Netherlands) to precisely synchronize our instruments based on the experiment's absolute time. In doing so, we could triangulate and visualize the data that we collected from the different measurement tools and indicators that constitute the basis of our construct measures.

4 Analysis and Results

4.1 Analysis

We processed answers to the first two questions in the questionnaire by simply counting how many times “yes” or “no” answers occurred. Because we did not plan the interview to directly test hypotheses but rather to gather some extra insights about participants' experience, we did not formally code the open-ended answers. We present descriptive statistics for the interview in Appendix E.

Regarding neurophysiological measures, we extracted facial analysis data from FaceReader. FaceReader calculated emotional valence as the intensity of “happy” emotion (i.e., positive emotion) minus the intensity of the negative expression (i.e., negative emotion) with the highest intensity. We used Acqknowledge to extract the data on EDA signal amplitude for all trials. We adjusted the EDA measures for baseline values to compute the EDA effects. For every trial (listening to a song), the baseline data provided the EDA just before the task. To make sure we captured participants' experience listening to music, we removed the five first and the five last seconds from each trial from the data and, thus, nuisance signals due to possible distraction at the start and the end of each song. For each endogenous construct (emotional valence and arousal), we conducted the core analyses using the group mean values.

As for the EEG analysis, we used Brainvision Analyzer (version three). We replicated EEG post-processing settings from Pauna et al. (2018). We filtered the EEG data and kept brain signals that ranged from 1 Hz to 50 Hz. In doing so, we could capture the main brain waves: Delta (1Hz-4Hz), Theta (4Hz-8Hz), alpha (8Hz-13Hz), and Beta (13Hz-25Hz) (Müller-Putz et al., 2015). Moreover, we applied a 256 Hz sampling rate. We removed eye blink-related artefacts (noise) and ran a Matlab Fourier transformation to extract the different frequency bands. We averaged electrode signals to extract trials' data. However, this processing revealed overly noisy EEG recorded signals, which meant we could not reasonably use the EEG data for our analyses. Hence, we did not use that data in our study. The vibro-kinetic chair's movements combined with participants' head movements likely caused the excessive signal noise. Still, because the EEG equipment added a few constraints such as restraining participants' movements during the task, we mention it to more completely describe the experimental settings.

We tested our hypotheses by running an analysis of covariance (ANCOVA) with repeated measures for self-reported data and an analysis of variance (ANOVA) with repeated measures for neurophysiological data. For personality-related effects, we ran statistical analyses using linear regression with random intercept models. The random intercept model accounts for non-measured participant-specific effects and suits repeated measure settings (“Mixed model”, 2021; Müller, Scealy, & Welsh, 2013). The model assumes no predictor to have a random effect. In all statistical analyses of psychometric data, we controlled for participants' previous experience with the songs (song known) and the extent to which they loved the songs (song loved) unlike with neurophysiological data-related analyses. Due to the explicit directions of our hypotheses, we used directional tests adjusted for multiple contrasts using Holm-Sidak method to control for type I errors. The experiment setup led to 96 trials in total. Based on the sample size, our test's statistical

power was 64 percent at $\alpha = 0.10$ to detect a medium effect size ($\omega^2 = 0.060$ or Cohen's $d = 0.5$) and 97 percent at $\alpha = 0.10$ to detect a high effect size ($\omega^2 = 0.150$ or Cohen's $d = 0.8$) (Cohen, 1988). Thus, our test had reasonable statistical significance despite the small sample size and there was a low risk of type I error in our study. We present descriptive statistics for the explicit and implicit measures for all dependent variables in Tables 2 and 3.

4.1.1 Assumptions of the Linear Models

Because we used parametric statistical models for our analyses, we checked for relevant assumptions. All analyses satisfied the normality assumption: data in all experimental conditions followed a normal distribution trend for all dependent variables (see Appendix B). On the other hand, the Mauchly's sphericity test lacked statistical significance (it satisfied the sphericity assumption) for self-reported emotional arousal ($p = 0.726$) and valence ($p = 0.671$) and for facial analysis-based valence ($p = 0.535$). However, EDA did not satisfy the sphericity assumption ($p = 0.051$). For unsatisfactory sphericity, we used Huynh-Feldt ANOVA results as Keppel and Wickens (2004) recommend.

Table 2. Descriptive Statistics (Self-reported Measures)

Conditions	Valence (self-reported)				Arousal (self-reported)			
	M_IT	M_NoIT	NoM_IT	Control	M_IT	M_NoIT	NoM_IT	Control
Min	3.00	1.00	2.67	1.00	1.00	1.00	1.00	1.00
Mean	5.88	5.18	5.29	5.35	4.05	3.58	3.27	4.20
Max	7.00	7.00	6.67	7.00	6.00	6.50	5.75	6.25
Std. dev.	1.15	1.68	.93	1.36	1.23	1.62	1.38	1.24

Abbreviations: cond. = conditions, con. = control, HFVKM = high-fidelity vibro-kinetic movement, std. dev. = standard deviation
Experimental treatments: M_IT = HFVKM & IT, M_NoIT = HFVKM & no IT, NoM_IT = no HFVKM & IT, control = no HFVKM & no IT.

Table 3. Descriptive Statistics (Neurophysiological Measures)

Conditions	Valence (facial analysis)				EDA			
	M_IT	M_NoIT	NoM_IT	Control	M_IT	M_NoIT	NoM_IT	Control
Min	-0.78	-0.98	-0.75	-0.84	-1.00	-0.99	-1.00	-0.99
Mean	-0.03	0.050	-0.048	-0.18	-0.37	-0.476	-0.380	-0.341
Max	0.55	0.48	0.47	0.37	0.59	0.44	0.59	0.36
Std. dev.	0.35	0.33	0.315	0.36	0.41	0.33	-0.34	0.36

Abbreviations: HFVKM = high-fidelity vibro-kinetic movement, std. dev. = standard deviation
Experimental treatments: M_IT = HFVKM & IT, M_NoIT = HFVKM & no IT, NoM_IT = no HFVKM & IT, control = no HFVKM & no IT.

4.2 Main Effects

We ran a two-way analysis of covariance (ANCOVA) with repeated measures on the questionnaire data using the two controls (song known, and song loved) as covariates. We found the ANCOVA for self-reported emotional valence to be significant: the HFVKM had a statistically significant main effect at $\alpha = 0.001$ ($p = 0.0005$, $F(1, 21) = 14.099$). Simple contrast analysis showed a significant difference between the means of the HFVKM and the no-HFVKM conditions at $\alpha = 0.001$ ($p = 0.0005$, $F(1, 21) = 14.099$). We recorded significantly more positive emotional valence in the condition with high-fidelity vibro-kinetic movement (HFVKM) than in the condition with no HFVKM with the mean difference's confidence interval (C.I.) (0.043, 0.375) not containing zero. Hence, we found support for H1a. For physiological data, a two-way ANOVA for emotional valence recorded using automatic facial analysis was significant at $\alpha = 0.05$ ($p = 0.015$; $F(1, 23) = 5.435$). Emotional valence was significantly higher in conditions with HFVKM than in conditions with no HFVKM ($p = 0.015 < 0.05$; C.I. = (0.033, 0.215) not containing zero), which suggests participants experienced significantly more positive affect from the vibro-kinetic movements and also supports H1a. More specifically, the M_NoIT condition spawned significantly more valence than the control condition at α

= 0.01 ($p = 0.001$; C.I. = (0.059, 0.397) not containing zero), while we observed no significant difference between the conditions with IT interactions (M_IT vs. NoM_IT).

Regarding self-reported emotional arousal, the ANCOVA that considered all IT conditions lacked significance. However, contrast analyses showed a significantly higher emotional arousal in the HFVKM condition than in the no-HFVKM condition both with IT-related interaction ($p = 0.022$) with the C.I. (0.236, 1.326) not containing zero. Additionally, in conditions without IT, the HFVKM condition spawned significantly less arousal than the no-HFVKM condition (M_NoIT vs. control; $p = 0.085 < 0.10$). Thus, self-reported data partially supported H1b since we found a difference in emotional arousal between multisensory and unisensory experiences only in conditions with no IT interactions. On the other hand, a two-way ANOVA for electrodermal activation (EDA) showed that the HFVKM did not have a statistically significant effect. However, simple contrast analysis showed that this result arose due to the non-significant difference between conditions with IT interaction (M_IT vs. NoM_IT): the HFVKM condition with no IT recorded significantly lower EDA than the control condition (M_NoIT vs. control; $p = 0.030$) with the C.I. (-0.251, -0.018) not containing zero. This result supports H1b, though we would need more statistical power to detect the HFVKM effect on EDA in situations with IT interactions. Table 4 summarizes the contrast analyses that we performed.

4.3 IT Interaction Moderation Effects

We ran a two-way ANCOVA with repeated measures on the self-reported data. For emotional valence, we found a significant interaction between the HFVKM and the IT factors at $\alpha = 0.05$ ($p = 0.010$; $F(1, 21) = 6.439$). Moreover, we found that the IT ($p = 0.225$; $F(1, 21) = 0.369$) did not have a significant main effect, which suggests IT-related interaction moderated the HFVKM's effect. Hence, the HFVKM factor did not have the same effect on participants' emotional valence in the IT compared to the no-IT condition. We ran a contrast analysis to check the direction of the IT moderation effect. Specifically, we ran a sample t-test to check the difference between the HFVKM factor's effect at the IT factor's two levels. The t-test lacked significance ($p = 0.928$; $t = 1.511$; C.I. (-0.101, 1.601)). Hence, we could not determine the direction of the IT moderation from the self-reported data on valence, which means we found partial support for H2a.

Looking at the physiological data, the two-way ANOVA for the emotional valence facial analysis showed a statistically significant interaction effect between the IT factors and the HFVKM ($p = 0.006$; $F(1, 23) = 0.006$). A sample t-test of interaction contrast on emotional valence dependent variable showed that the HFVKM factor had a statistically higher effect in the absence of IT interactions than in the presence of IT interaction ($p = 0.006$; $t = -2.726$; C.I. = (-0.340, -0.078) not containing zero). Moreover, as expected, the IT factor's direct effect lacked statistical significance ($p = 0.327$; $F(1, 23) = 0.206$). Consequently, we found support for H2a.

On the other hand, for self-reported emotional arousal, a two-way ANCOVA with repeated measures showed a significant interaction between IT factors and the HFVKM ($p = 0.079 < 0.10$; $F(1, 21) = 2.154$). An interaction contrast analysis showed that the HFVKM factor had a significantly higher arousal effect with IT compared to without IT interaction ($p = 0.007$; $t = 2.665$; C.I. (0.500, 2.303) not containing zero). In other words, in the absence of IT interactions, the HFVKM induced significantly higher arousal than in the presence of IT interactions. Also, as we expected, the IT factor did not have a direct effect on participant's perceptual emotional arousal ($p = 0.428$; $F(1, 21) = 0.034$). As a result, we found the IT factor to have a positive moderation effect, which supports H2B.

Regarding electrodermal activation, two-way ANOVA highlighted a statistically significant interaction effect between the HFVKM and the IT factor ($p = 0.053 < 0.10$; $F(1, 23) = 2.824$). An interaction contrast analysis showed a statistically significant lower decrease in participants' EDA due to the HFVKM factor in the presence of IT interactions than in the absence of IT interactions ($p = 0.053 < 0.10$; $t = 1.680$; C.I. (-0.003, 0.300)). Additionally, as expected, we found that the IT factor had no main effect ($p = 0.294$; $F(1, 23) = 0.303$). These results suggest that IT-related interaction had a negative moderation impact on the HFVKM factor's effect on emotional arousal (weaker effect with IT interactions), which supports H2b. We present the interaction contrast analyses that we performed in Table 3, the interaction effects in Figure 4, and summary model statistics in Appendix C.

To visualize the participants' experiences, we depict Thayer's arousal-valence emotional plan in Figure 5 (Yang, Lin, Su, & Chen, 2008). In the figure, we show the self-reported and physiological data for all four experimental conditions. We include this emotional plane not to directly match or test the hypotheses but to visually show the best emotional positions as per our operationalization. Clearly, regarding implicit

measures, the M_NoIT condition provided the lowest emotional arousal and the highest positive affect (i.e., the best hedonic experience). However, self-reported measures showed the highest valence in the M_IT condition and the lowest emotional arousal in the NoM_IT condition, unlike the implicit measures.

Table 4. Contrast Analysis for Main and Moderation Effects

Dependent variable	Contrast	Means' difference	P-value	Confidence interval	Cohen's d	Hypothesis tested
Valence (self-reported)	Mean _{HFVKM} - Mean _{NoHFVKM} ****	0.209	0.0005	(0.043, 0.375)	0.159	H1a
	M_IT – NoM_IT **	0.584	0.023	(0.111, 1.057)	0.444	H1a
	M_NoIT – Control	-0.167	0.318	(-0.763, 0.430)	0.127	H1a
	(M_IT – NoM_IT) – (M_NoIT – control) (t = 1.511)	0.750	0.928	(-0.101, 1.601)	0.570	H2a
Arousal (self-reported)	Mean _{HFVKM} - Mean _{NoHFVKM}	0.081	0.236	(-0.384, 0.546)	0.058	H1b
	M_IT – NoM_IT **	0.781	0.022	(0.236, 1.326)	0.555	H1b
	M_NoIT – Control *	-0.620	0.085	(-0.931, -0.309)	0.441	H1b
	(M_IT – NoM_IT) – (M_NoIT – control) *** (t = 2.665)	1.401	0.007	(0.500, 2.303)	0.996	H2b
Arousal (EDA)	Mean _{HFVKM} - Mean _{NoHFVKM}	-0.060	0.235	(-0.145, 0.24)	0.165	H1b
	M_IT – NoM_IT	0.014	0.416	(-0.095, 0.125)	0.039	H1b
	M_NoIT – Control **	-0.135	0.030	(-0.251, -0.018)	0.372	H1b
	(M_IT – NoM_IT) – (M_NoIT – control) * (t = 1.680)	0.148	0.053	(-0.003, 0.300)	0.408	H2b
Valence (facial analysis)	Mean _{HFVKM} - Mean _{NoHFVKM} **	0.124	0.015	(0.033, 0.215)	0.360	H1a
	M_IT – NoM_IT	0.020	0.383	(-0.147, 0.186)	0.058	H1a
	M_NoIT – Control ***	0.228	0.001	(0.059, 0.397)	0.663	H1a
	(M_IT – NoM_IT) – (M_NoIT – Control) *** (t = -2.726)	-0.209	0.006	(-0.340, -0.078)	0.608	H2a

* = significant at $\alpha = 0.10$; ** = significant at $\alpha = 0.05$; *** = significant at $\alpha = 0.01$; **** = significant at $\alpha = 0.001$
M_IT = HFVKM & IT, M_NoIT = HFVKM & no IT, NoM_IT = no HFVKM & IT, control = no HFVKM & no IT, MeanHFVKM = mean of the "HFVKM" condition, MeanHFVKM = mean of the no-HFVKM condition.
Cohen's d statistic is the effect size and it is based on the population's standard deviation for each dependent variable.

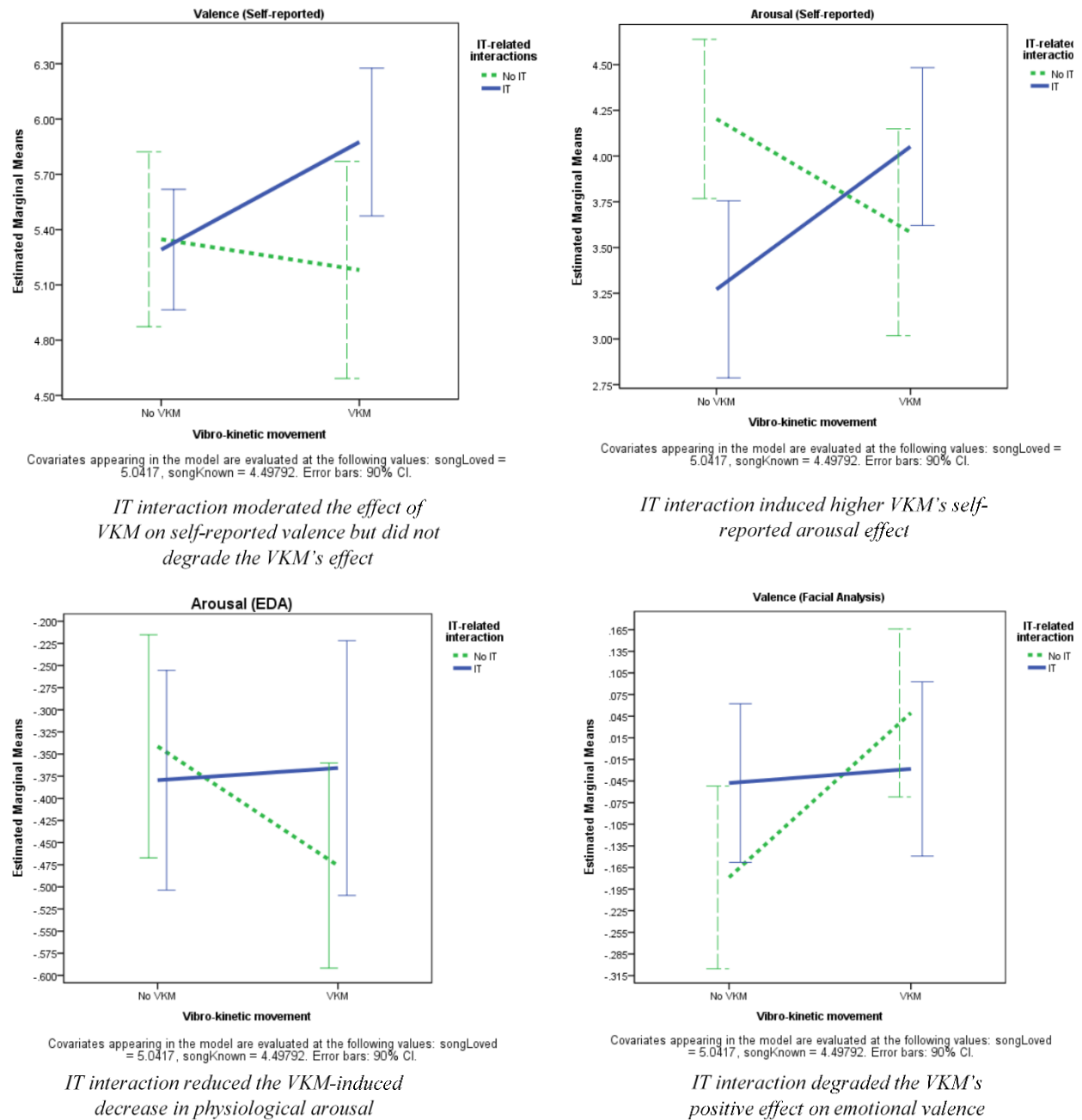
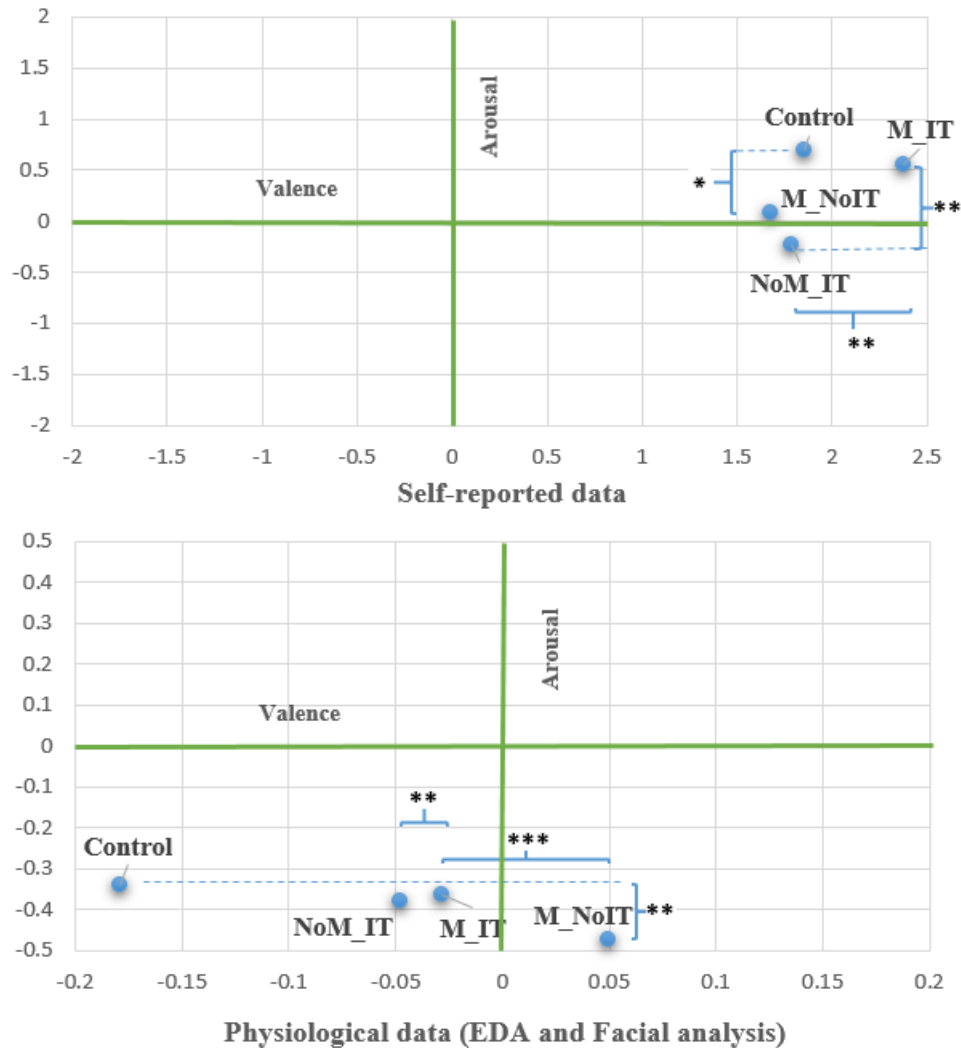


Figure 4. Interaction Effect (HFVKM * IT)



* = significant at $\alpha = 0.10$; ** = significant at $\alpha = 0.05$; *** = significant at $\alpha = 0.01$
M IT = HFVKM & IT. M NoIT = HFVKM & no IT. NoM IT = no HFVKM & IT. control = no HFVKM & no

Figure 5. Thayer's Arousal-Valence Emotional Plane

4.4 Moderated Moderation by Personality Traits

Regarding personality-related specificities, we found that extraversion or neuroticism had no main effect. Likewise, we found no two-way interaction between personality traits (extraversion or neuroticism) and the HFVKM or the IT factor. Regarding extraversion, while we found no significant three-way interaction effect for self-reported emotional valence and facial analysis-related valence (which does not support H3a), we observed three-way interaction effects for emotional arousal. Self-reported data on emotional arousal showed a significant three-way interaction effect ($p = 0.064$; $\beta = 0.295$; $t = 1.590$). This result suggests that, overall, higher extraversion was associated with a stronger HFVKM*IT interaction effect on self-reported emotional arousal (i.e., stronger negative moderation by IT interaction), which supports H3b. Moreover, in the control condition, extraversion was associated with lower self-reported emotional arousal ($p = 0.048$; $t = -1.755$) compared to the other conditions, which suggests that the two stimuli (HFVKM and IT) induced extraversion's higher overall association with arousal. Concerning physiological data, we found a three-way interaction effect for EDA with regard to extraversion ($p = 0.016$; $\beta = 0.064$; $t = 2.290$), which supports H3b. Moreover, we generally observed extraversion to be positively associated with EDA ($p = 0.088$; $t = 1.367$).

Regarding neuroticism, self-reported valence data showed a non-statistically significant three-way interaction. Likewise, facial analysis-related valence data showed a non-statistically significant three-way interaction. However, we found neuroticism to be associated with more emotional valence only in the control condition ($p = 0.081$; $t = 1.456$), which suggests a degrading effect when we combined the neuroticism factor with the HFVKM and IT. We illustrate this observation in Appendix D, which depicts a neuroticism*HFVKM*IT three-way interaction that partially supports H4a. Furthermore, we found the three-way interaction for self-reported emotional arousal data to be not significant. However, EDA data showed a significant three-way interaction ($p = 0.018$; $\beta = 0.072$; $t = 2.240$). Moreover, the fine-grained analysis revealed that neuroticism was significantly associated with more electrodermal activation in the condition with the HFVKM and IT stimuli ($p = 0.025$; $t = 2.082$) compared to the control condition. Hence, we also found support for H4b. We summarize the three-way interaction effects in Table 5. We graphically depict all three-way interactions in Appendix D. Finally, we summarize the results for each hypothesis in Table 6.

Table 5. Three-way Interactions Summary Model Statistics

Factor	Estimated effect	Std. error	t-value	p-value	CI	Dependent variable
Neuroticism*HFVKM*IT	-0.027	0.138	0.200	0.423	(-0.265, 0.211)	Arousal (self-reported)
Neuroticism*HFVKM*IT	0.072	0.032	2.240	0.018	(0.017, 0.128)	EDA
Neuroticism*HFVKM*IT	-0.007	0.033	-0.200	0.423	(-0.063, 0.050)	Valence (facial analysis)
Neuroticism*HFVKM*IT	0.034	0.111	0.310	0.382	(-0.159, 0.227)	Valence (self-reported)
Extraversion*HFVKM*IT	0.295	0.185	1.590	0.064	(-0.025, 0.615)	Arousal (self-reported)
Extraversion*HFVKM*IT	0.064	0.028	2.290	0.016	(0.016, 0.111)	EDA
Extraversion*HFVKM*IT	0.006	0.029	0.200	0.421	(-0.045, 0.056)	Valence (facial analysis)
Extraversion*HFVKM*IT	0.196	0.196	1.000	0.164	(-0.142, 0.534)	Valence (self-reported)

5 Discussion

In this study, we examine the role that information technology (IT) can play in how much pleasure people experience during hedonic activities (especially multisensory activities that involve touching, listening, and watching) when using IT to multitask. Based on the model we developed, we found that IT-related multitasking impeded the positive hedonic experience that the multisensory activity generated. Specifically, we found that a more positive hedonic experience was associated with higher emotional valence (positive affect) and lower emotional arousal. Generally, our results align with the effects we hypothesized.

5.1 Findings

5.1.1 Direct Influences

Regarding the generated positive hedonic experience, we found significant support for H1a when considering emotional valence using both self-reported and physiological (automatic facial analysis) measures. In other words, the HFVK armchair induced higher emotional valence (positive affect) in line with past studies that suggest a multisensory hedonic activity (compared to a unisensory activity) has a positive effect on hedonic experience (e.g., Giroux et al., 2019; Pauna et al., 2018; Donley et al., 2014). However, this effect's magnitude differed between explicit and implicit measures. When participants listened to music in the armchair, they physiologically experienced moderately higher overall positive affect as evidenced by the small effect size (Cohen's $d = 0.36$), but the effect size's magnitude increased considerably when they did not multitask with IT. On the other hand, self-reported measures suggest that when participants listened to music with the armchair's HFVKM, they perceived only slightly higher positive affect overall as the non-practical effect has indicated (Cohen's $d = 0.16$), but the effect size increased when they multitasked with IT (Cohen's $d = 0.44$).

The findings concur with participants' post-experiment feedback. Generally, participants reported having undergone a positive experience, and all but one reported wanting to experience the vibro-kinetic hedonic chair again. The synchronicity between the different stimuli that the hedonic activity generated partially explains this trend: the fact the vibro-kinetic movements and vibrations that the armchair generated perfectly aligned with the songs made them enhance the music listening experience (i.e., it improved results

compared to the unisensory setting). As a participant said: It was really fun that the movements and vibrations were traced on the song". This factor predominantly explained the enjoyment that participants reported during the interview. Indeed, we further confirmed as much in the statistical results, which showed significantly more positive experience in the multisensory (HFVKM) condition. In this condition, participants experienced higher positive affect and, when no IT interactions interfered with the hedonic activity, experienced lower arousal than in the unisensory condition in line with the purpose of relaxing.

Table 6. Hypothesis Testing Results Summary (All Methods)

Hypothesis	Dependent variable	Method	Support
H1a	Emotional valence	Self-reported	Yes
		Facial analysis	Yes
H1b	Emotional arousal	Self-reported	Partial
		EDA	Partial
H2a	Emotional valence	Self-reported	Partial
		Facial analysis	Yes
H2b	Emotional arousal	Self-reported	Yes
		EDA	Yes
H3a	Emotional valence	Self-reported	No
		Facial analysis	No
H3b	Emotional arousal	Self-reported	Yes
		EDA	Yes
H4a	Emotional valence	Self-reported	No
		Facial analysis	Partial
H4b	Emotional arousal	Self-reported	No
		EDA	Yes

5.1.2 Moderating Impact of IT Interactions

Regarding the moderation effect, we observed that IT interaction had a general degrading effect on the positive experience that the multisensory activity generated. We found support for H2a and H2b: when participants multitasked with the IT, they experienced lower positive affect physiologically, a considerable effect that the medium effect size indicates (Cohen's $d = 0.61$). In the same conditions, participants perceived higher arousal to a great extent as the large effect size we recorded has indicated (Cohen's $d = 1$) in addition to a considerably higher physiological arousal indicated by the medium effect size (Cohen's $d = 0.41$). The lower positive affect and higher arousal that we obtained from the implicit measures suggest that participants experienced a loss in their positive hedonic experience that the HFVKM generated without their awareness. Two observations further support moderation. First, as we report in Section 4 for self-reported arousal, while the HFVKM factor had a significant positive effect on the hedonic experience (lower arousal) in the absence of IT interaction, in the presence of IT interactions, the HFVKM factor had a significant negative effect on the hedonic experience. Second, while facial analyses suggest that the HFVKM factor spawned significantly higher positive affect in the absence of IT interaction, we observed that it had no significant effect in the presence of IT interactions. This observation suggests that IT interactions were detrimental to the relaxing activity.

On the other hand, our results about perceived affect (H2a) support the IT factor's moderating role but do not allow for conclusions on the moderation's direction. We suggest the following ideas as possible explanations for this observation. As Figure 5 depicts (self-reported measures), when participants listened to music while using the HFVKM armchair, we observed higher relaxation (lower arousal) in the no-IT condition (M_NoIT) than in the condition with IT-related interaction (M_IT) as we expected. However, unlike our expectations, participants reported more (though non-statistically significant) positive valence in the M_IT condition than in the M_NoIT condition (which they perceived as more relaxing). The nature of the IT stimulus, which provided content that participants may have been pleased with, may explain why. Participants may have been absorbed with the IT task because they enjoyed discovering interesting information on the mobile application about each song being listened to. As some participants reported,

they could have used the mobile application for fun. Moreover, due to the IT stimulus's pleasing nature, the IT interactions may have distracted the participants so much that they often forgot about the HFVKM. For instance, one participant said: "Only after answering the question did I realize that I missed the vibrations [due to the application]". Considering these explanations, the non-significance of the IT moderation's observed direction in the case of perceptual affect appears plausible.

Furthermore, the Thayer's emotional plan in Figure 5 with physiological data revealed that the self-reported emotional valence in condition with IT did not align with what the participants experienced physiologically. Actually, with regard to the physiological data, the HFVKM condition with no IT-related interaction captured the best experience (i.e., in the M_NoIT condition in the quadrant associated with the best relaxing hedonic experience (the highest emotional valence and the lowest emotional arousal)). Moreover, we found a non-significant difference between the conditions with IT-related interaction, which suggests that IT degraded the hedonic experience to the extent that the armchair's perfectly synchronized HFVKM had a negligible effect with respect to arousal and valence. Interview data support this finding. For example, participants made typical comments such as:

Also there is the fact that you ask me to use this [the mobile application], so I could not really focus on the chair, I totally forget that it exists, I am more interested in the app"

It's only upon filling to the questionnaire that I wondered whether I had noticed vibrations [and movements]. I was really focused on the [mobile] app.

The best multisensory hedonic experience happened with the HFVKM and, importantly, when participants fully immersed themselves in the activity without any IT interaction.

Regarding the IT-related multitasking condition (nM_IT in Figure 5) in which the participants reported the highest perceived emotional valence, the fact that this result does not align with the physiological emotional valence suggests the following interpretations. First, although the implicit measures suggested otherwise, in reality, participants were not happier when they used the IT while listening to music with the HFVKM than the chair generated even though they thought they were happier in this condition. This finding concurs with why we conducted our study: to explore the fact that digital natives (similar to the participants in our study) tend to believe that they are good at multitasking (Carrier, Rosen, Cheever, & Lim, 2015) even though the literature suggests that such behavior has an adverse effect (Gazzaley & Rosen, 2016; Strayer & Watson, 2016; Rosen, 2008; Bawden & Robinson, 2008; D'Arcy et al., 2014). The IS literature has made a theoretical distinction between emotional affect and perceived affect. In her affective concept taxonomy, Zhang (2013) proposes that researchers should consider the affective response to a stimulus as two conceptually distinct types; namely, emotions and affective stimulus evaluation. Zhang (2013) suggests that emotions constitute episodic affective states that a stimulus induces in the form of neurophysiological states. However, she defines affective evaluation as individuals' assessment of a stimulus' ability to impact their emotions (e.g., "my music listening experience on the vibro-kinetic chair was pleasant"). Interestingly, affective evaluation may happen with or without accompanying emotions (Zhang, 2013; Russell, 2003). This conceptual distinction suggests that emotional valence, which we captured with implicit measures, may not represent the same construct as self-reported valence, which we captured through psychometric measures such as affective assessment of participants' experience (see Appendix A). Second, the IS literature suggests that implicit measures and explicit measures do not substitute for but complement each other as they allow one to explain variance in IS constructs distinctively (Tams et al., 2014). Hence, explicit measures may help explain some aspects that one may not be able to capture with implicit measures. For instance, explicit measures suggest that, as participants liked the IT because it satisfied their natural desire to seek more information about their hedonic experience and, thus, more enjoyment (Jeong & Fishbein, 2007), they thought they were happier during the IT-related multitasking condition, unlike the emotions they experienced physiologically.

These findings align with past research that suggests that multitasking with IT does degrade individuals' performance and attention (Bawden & Robinson, 2008; D'Arcy et al., 2014). In line with flow theory, the fact that IT interactions constituted interruptions (e.g., Gazzaley & Rosen, 2016) to the main activity in our experiment can explain this adverse effect; consequently, IT interactions impeded participant's ability to reach flow states in which participants would likely have experienced maximum pleasure and enjoyment (Csikszentmihályi, 1990). Moreover, this finding concurs with dual-task interference theory: participants experienced a cognitive cost to switch their attention between listening to the music on the multisensory chair and interacting with the IT.

Finally, we detected medium to large IT moderation effect sizes (Cohen's d ranging between 0.408 and 0.996; see Table 3) in line with the planned statistical power. A large effect size corresponds to Cohen's d greater or equal to 0.8 (Cohen, 1988).

5.1.3 Considerations Related to Personality

We observed that participants with higher extraversion scores generally experienced higher physiological activation. Moreover, our results suggest that, as per the explicit and implicit measures, higher extraversion scores were associated with the IT factor having a stronger negative moderation effect on emotional arousal. Hence, IT-related interaction degraded the hedonic experience of individuals higher in extraversion more than for individuals lower in extraversion in that the interaction induced the HFVKM to have a higher emotional arousal effect on the former. These results align with the literature that suggests that, when a stressor stimulates extraverts, one can expect them to exhibit higher physiological arousal (Schneider et al., 2012) or higher stress (Swickert et al., 2002; Loerbroks et al., 2009).

Concerning the neuroticism personality dimension, the findings we obtained from analyzing our neurophysiological data suggest that the stimuli degraded positive affect. Moreover, a higher neuroticism score was associated with the IT interaction having a stronger negative moderation effect on the HFVKM's (negative) effect on emotional arousal. This finding suggests that IT interaction more strongly deteriorated the relaxing effect that the HFVKM induced for participants higher in neuroticism. Furthermore, higher neuroticism was associated with higher emotional arousal in the stimuli's presence. These findings align with past research that suggests that neuroticism is negatively associated with positive affect (Feng et al., 2015; Gross, Sutton, & Ketelaar, 1998) and that people higher in neuroticism experience a more sensitive increase in negative affect in response to a stressor (Schneider et al., 2012). Furthermore, research has positively associated neuroticism with stress (Mark et al., 2014), which researchers have operationalized as physiological activation (Loerbroks et al., 2009; Riedl, 2013). Hence, when exposed to a stimulus, one can expect people high in neuroticism to experience higher stress through higher physiological activation. As we observed, people high in neuroticism tend to display higher negative emotional reactivity to stimuli.

5.2 Limitations and Future Directions

As with any study, ours has several limitations. First, we asked people to keep their eyes open for each song's full duration. As neuroscience research suggests, when individuals close their eyes while resting, the amount of alpha waves in the brain increases, which suggests higher relaxation states (Müller-Putz et al., 2015). Moreover, research has shown closing one's eyes in resting conditions to be directly associated with skin conductance level (SCL), a long-established method to measure arousal (Barry & De Blasio, 2018). We can contend that, if we had allowed participants to close their eyes in our experiment, our experimental task would likely have generated even more participant relaxation and lower emotional arousal for a better experience. However, participants could only perform the IT-related activity in our study (i.e., interacting with the mobile application) with open eyes. In any case, open eyes cause a decrease in alpha frequency band and an increase in physiological arousal (Barry & De Blasio, 2018). Hence, had we performed our experiment with participants closing their eyes as they listened to music in conditions with no IT-related interference, we would have arguably found even more significant effects. As an illustration, 54 percent of the participants mentioned that they would have preferred listening to the music with their eyes closed. As for why, they provided reasons such as to focus more, to immerse themselves more, to listen to the songs more calmly, or to relax more. Hence, future research on relaxing hedonic activities using neurophysiological tools such as EEG, galvanometer, and automatic facial analysis could consider making participants perform tasks with closed eyes.

In addition, we considered multisensory hedonic activities that focused on relaxation. Hence, we found it reasonable to associate positive experience with higher emotional valence, lower emotional arousal, and higher relaxation. As for hedonic activities that focus on stimulation (e.g., playing video games, board games, dancing), future studies could associate a positive experience with different levels of emotional dimensions depending on the activity.

Finally, we did not plan to conduct comprehensive qualitative analyses. We could have further supported our hypotheses qualitatively had we collected more relevant qualitative data. Moreover, richer qualitative data would have provided even more insights to understand our non-significant results. For example, had we collected data about the extent to which participants appreciated the IT stimulus, we may have learned more about how much participants were pleased with using the IT device impacted the IT interaction factor's moderation effect regarding self-reported emotional valence.

5.3 Contributions

Based on our findings, we recommend that individuals may enjoy a better hedonic experience when they avoid multitasking at the same time with IT as people commonly do (with IT not being central to the hedonic activity). When individuals multitask with information technology, the technologies will likely act as an important distraction that diverts their focus from a hedonic activity. Given technology's omnipresent nature, people should recognize its adverse effects, which much research has emphasized (e.g., D'Arcy et al., 2014; Bawden & Robinson, 2008). Moreover, people should be mindful about the adverse effects that can result from multitasking with IT during their leisure time. The findings from this study suggest that people higher in extraversion or neuroticism experience more degraded relaxing experiences when they display such multitasking-related behaviors. Hence, people should seriously consider adjusting their leisure behavior to maximize the benefit of engaging in hedonic activities.

All in all, we make five contributions to the literature with this study. First, we fill a research gap in understanding multitasking during leisure activities given that research has generally focused on professional contexts in the past. Second, our findings show information technology's deteriorating effect on individuals when they use it to multitask during hedonic activities that focus on relaxing. Third, our findings suggest the value that multisensory activities (compared to unisensory activities) add to leisure experience by empirically showing they create specific positive hedonic experience effects. In other words, they convey the idea that combining different enjoyment stimuli may benefit hedonic experiences. Fourth, our personality-related investigations suggest that individuals vary in their vulnerability to multitasking with IT during leisure based on personality traits. However, we suggest that researchers conduct follow-up studies with a bigger sample to obtain significant power to detect a richer set of personality impacts. However, our preliminary significant findings represent an important motivation for researchers to investigate personality impacts in the context we considered in this study. Finally, our study empirically illustrates the conceptual distinction between self-reported emotional valence (or affective evaluation) and the neurophysiological manner in which emotions manifest as past research, such as seminal works on conceptualizing emotion (e.g., Zhang, 2013; Tams et al., 2014), has suggested. Our work helps explain why people could report different affects than actually and physiologically observed emotional states.

6 Conclusion

This study represents one of few research to investigate the impact that multitasking with information technologies has on individuals in hedonic settings. Past research on multitasking mainly focuses on professional contexts. Specifically, we examined the extent to which multitasking with IT influences hedonic experience that focuses on relaxing. Using explicit (self-reported) and implicit measures (electrodermal activity and automatic facial analysis) to examine hedonic experience in an experimental study, we found considerable outcomes. Specifically, we found IT to be significantly detrimental to participants' positive hedonic experience that a multisensory music listening activity generated. Furthermore, we found that multitasking with IT had a more adverse effect on people high in extraversion and neuroticism. We call for people to remember our findings during their leisure time and to keep their technology devices away from their central hedonic activities as much as possible. Future research may investigate multitasking with IT in hedonic settings that focus on stimulation or excitement as opposed to relaxation.

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References

- Addas, S., & Pinsonneault, A. (2018). E-mail interruptions and individual performance: Is there a silver lining? *MIS Quarterly*, 42(2), 381-405.
- Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, 24(4), 665-694.
- Anderson, B. B., Jenkins, J. L., Vance, A., Kirwan, C. B., & Eargle, D. (2016). Your memory is working against you: How eye tracking and memory explain habituation to security warnings. *Decision Support Systems*, 92, 3-13.
- Barry, R. J., & De Blasio, F. M. (2018). Natural frequency components in the resting (eyes-open and -closed) EEG and their links to arousal. *International Journal of Psychophysiology*, 131, S62.
- Bawden, D., & Robinson, L. (2008). The dark side of information: Overload, anxiety and other paradoxes and pathologies. *Journal of Information Science* 35(2), 180-191.
- Becker, M., Alzahabi, R., & Hopwood, C. (2018). Media multitasking is associated with symptoms of depression and social anxiety. *Computers in Human Behavior*, 81, 115-123.
- Bennett, S., & Maton, K. (2010). Beyond the "digital natives" debate: Towards a more nuanced understanding of students' technology experiences. *Journal of Computer Assisted Learning*, 26(5), 321-331.
- Boulais, S., Lizotte, J. M., Trottier, S., & Gagnon, S. (2011). U.S. Patent No. 7,934,773. Washington, DC: U.S. Patent and Trademark Office.
- Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25(1), 49-59.
- Bynion, T. M., & Feldner, M. T. (2017). *Self-assessment manikin*. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of personality and individual differences*. Cham, Switzerland: Springer.
- Cameron, A., Barki, H., Ortiz de Guinea, A., Coulon, T., & Moshki, H. (2018). Multicommunicating in meetings: Effects of locus, topic relatedness, and meeting medium. *Management Communication Quarterly*, 32(3), 303-336.
- Cameron, A., & Webster, J. (2013). Multicommunicating: Juggling multiple conversations in the workplace. *Information Systems Research*, 24(2), 352-371.
- Carrier, L. M., Cheever, N. A., Rosen, L. D., Benitez, S., & Chang, J. (2009). Multi-tasking across generations: Multi-tasking choices and difficulty ratings in three generations of Americans. *Computers in Human Behavior*, 25(2), 483-489.
- Carrier, L. M., Rosen, L. D., Cheever, N. A., & Lim, A. F. (2015). Causes, effects, and practicalities of everyday multitasking. *Developmental Review*, 35, 64-78.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: L. Erlbaum Associates.
- Combes, B. (2006). Techno savvy or techno oriented: Who are the Net generation? In *Proceedings of Asia-Pacific Conference on Library and Information Education and Practice*.
- Csikszentmihalyi, M. (1988). *The flow experience and its significance for human psychology*. In M. Csikszentmihalyi & I. S. Csikszentmihalyi (Eds.), *Optimal experience: Psychological studies of flow in consciousness* (p. 15-35). Cambridge, UK: Cambridge University Press.
- Czikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. *Journal of Leisure Research*, 24(1), 93-94.
- D'Arcy, J., Gupta, A., Tarafdar, M., & Turel, O. (2014). Reflecting on the "dark side" of information technology use. *Communications of The Association for Information Systems*, 35, 109-118.
- Deng, L., & Poole, M. (2010). Affect in web interfaces: A study of the impacts of web page visual complexity and Order. *MIS Quarterly*, 34(4), 711-730.

- Dimoka, A., Davis, F. D., Gupta, A., Pavlou, P. A., Banker, R. D., Dennis, A. R., Ischebeck, A., Müller-Putz, G., Benbasat, I., Gefen, D., Kenning, P. H., Riedl, R., vom Brocke, J., & Weber, B. (2012). On the use of neurophysiological tools in IS research: Developing a research agenda for neuroIS. *MIS Quarterly*, 36(3), 679-702.
- Donley, J., Ritz, C., & Shujau, M. (2014). Analysing the quality of experience of multisensory media from measurements of physiological responses. In *Proceedings of the 2014 Sixth International Workshop on Quality of Multimedia Experience*.
- Ekman, P., & Friesen, W. V. (1978). *Facial action coding system: A technique for the measurement of facial movement*. Palo Alto, CA: Consulting Psychologists Press.
- Feng, C., DeMarco, A. C., Haroon, E., & Rilling, J. K. (2015). Neuroticism modulates the effects of intranasal vasopressin treatment on the neural response to positive and negative social interactions. *Neuropsychologia*, 73, 108-115.
- Fenko, A., Kersten, L., & Bialkova, S. (2016). Overcoming consumer scepticism toward food labels: The role of multisensory experience. *Food Quality and Preference*, 48, 81-92.
- Francis, L. J., Brown, L. B., & Philipchalk, R. (1992). The development of an abbreviated form of the revised Eysenck personality questionnaire (EPQR-A): Its use among students in England, Canada, the U.S.A. and Australia. *Personality and Individual Differences*, 13(4), 443-449.
- Gardé, A., Léger, P. M., Sénécal, S., Fredette, M., Chen, S. L., Labonté-Lemoyne, É., & Ménard, J. F. (2018a). Virtual reality: Impact of vibro-kinetic technology on immersion and psychophysiological state in passive seated vehicular movement. In *Proceedings of the International Conference on Human Haptic Sensing and Touch Enabled Computer Applications*.
- Gardé, A., Léger, P. M., Sénécal, S., Fredette, M., Labonté-Lemoyne, E., Courtemanche, F., & Ménard, J. F. (2018b). The effects of a vibro-kinetic multi-sensory experience in passive seated vehicular movement in a virtual reality context. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*.
- Gazzaley, A., & Rosen, L. D. (2016). *The distracted mind: Ancient brains in a high-tech world*. Cambridge, MA: MIT Press.
- Gerber, A. S., Huber, G. A., Doherty, D., Dowling, C. M., & Ha, S. E. (2010). Personality and political attitudes: Relationships across issue domains and political contexts. *American Political Science Review*, 104(1), 111-133.
- Giroux, F., Boasen, J., Senecal, S., Fredette, M., Tchanou, A. Q., Menard, J., Paquette, M., Léger, P. (2019). Haptic stimulation with high fidelity vibro-kinetic technology psychophysiologicaly enhances seated active music listening experience. In *Proceedings of the IEEE World Haptics Conference*.
- Gomez, R., Cooper, A., & Gomez, A. (2000). Susceptibility to positive and negative mood states: Test of Eysenck's, Gray's and Newman's theories. *Personality and Individual Differences*, 29(2), 351-365.
- Grimm, M., & Kroschel, K. (2005). Evaluation of natural emotions using self-assessment manikins. In *Proceedings of the IEEE Workshop on Automatic Speech Recognition and Understanding*.
- Gross, J. J., Sutton, S. K., & Ketelaar, T. (1998). Relations between affect and personality: Support for the affect-level and affective-reactivity views. *Personality and Social Psychology Bulletin*, 24(3), 279-288.
- Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York, NY: The Guilford Press.
- Higgins, E. T. (2006). Value from hedonic experience and engagement. *Psychological Review*, 113(3), 439.
- Iluguru. (n.d.). *Eysenck's personality inventory (EPI) (extroversion/introversion)*. Retrieved from <http://www.iluguru.ee/test/eysencks-personality-inventory-epi-extroversionintroversion/>
- Jenkins, J. L., Anderson, B. B., Vance, A., Kirwan, C. B., & Eargle, D. (2016). More harm than good? How messages that interrupt can make us vulnerable. *Information Systems Research*, 27(4), 880-896.
- Jeong, S. H., & Fishbein, M. (2007). Predictors of multitasking with media: Media factors and audience factors. *Media Psychology*, 10(3), 364-384.

- Juslin, P. N. (2000). Cue utilization in communication of emotion in music performance: Relating performance to perception. *Journal of Experimental Psychology: Human Perception and Performance*, 26(6), 1797-1812.
- Kaplan, S. C., Levinson, C. A., Rodebaugh, T. L., Menatti, A., & Weeks, J. W. (2015). Social anxiety and the big five personality traits: The interactive relationship of trust and openness. *Cognitive Behaviour Therapy*, 44(3), 212-222.
- Keppel, G., & Wickens, T. (2004). *Design and analysis: A researcher's handbook*. Upper Saddle River, NJ: Pearson/Prentice Hall.
- Kuppens, P., Tuerlinckx, F., Russell, J. A., & Barrett, L. F. (2013). The relation between valence and arousal in subjective experience. *Psychological Bulletin*, 139(4), 917-940.
- Küssner, M. B. (2017). Eysenck's theory of personality and the role of background music in cognitive task performance: A mini-review of conflicting findings and a new perspective. *Frontiers in Psychology*, 8.
- Leger, K. A., Charles, S. T., Turiano, N. A., & Almeida, D. M. (2016). Personality and stressor-related affect. *Journal of Personality and Social Psychology*, 111(6), 917-928.
- Lempert, K. M., & Phelps, E. A. (2014). Neuroeconomics of emotion and decision making. In P. W. Glimcher & E. Fehr (eds). *Neuroeconomics: Decision making and the brain* (pp. 219-236). Waltham, MA: Academic Press.
- Lewinski, P., Fransen, M. L., & Tan, E. S. H. (2014). Predicting advertising effectiveness by facial expressions in response to amusing persuasive stimuli. *Journal of Neuroscience, Psychology, and Economics*, 7(1), 1-14.
- Loerbroks, A., Apfelbacher, C. J., Thayer, J. F., Debling, D., & Sturmer, T. (2009). Neuroticism, extraversion, stressful life events and asthma: A cohort study of middle-aged adults. *Allergy*, 64(10), 1444-1450.
- Logan, H., Lutgendorf, S., Rainville, P., Sheffield, D., Iverson, K., & Lubaroff, D. (2001). Effects of stress and relaxation on capsaicin-induced pain. *Journal of Pain*, 2(3), 160-170.
- Mark, G., Wang, Y., & Niiya, M. (2014). Stress and multitasking in everyday college life: An empirical study of online activity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.
- René, M., & Ivanoff, J. (2005). Capacity limits of information processing in the brain. *Trends in Cognitive Sciences*, 9(6), 296-305.
- Martinez, B., Valstar, M. F., Jiang, B., & Pantic, M. (2017). Automatic analysis of facial actions: A survey. *IEEE Transactions on Affective Computing*, 10(3), 325-347.
- McGlynn, F. D., Moore, P. M., Rose, M. P., & Lazarte, A. (1995). Effects of relaxation training on fear and arousal during in vivo exposure to a caged snake among DSM-III-R simple (snake) phobics. *Journal of Behavior Therapy and Experimental Psychiatry*, 26(1), 1-8.
- Mesmer-Magnus, J., Viswesvaran, C., Bruk-Lee, V., Sanders, K., & Sinha, N. (2014). Personality correlates of preference for multitasking in the workplace. *Journal of Organizational Psychology*, 14(1), 67-76.
- Mixed model. (2021). In *Wikipedia*. Retrieved from https://en.wikipedia.org/w/index.php?title=Mixed_model&oldid=1023349557
- Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192-222.
- Moran, R. J., Molholm, S., Reilly, R. B., & Foxe, J. J. (2008). Changes in effective connectivity of human superior parietal lobule under multisensory and unisensory stimulation. *European Journal of Neuroscience*, 27(9), 2303-2312.
- Müller, S., Scea, J., & Welsh, A. (2013). Model selection in linear mixed models. *Statistical Science*, 28(2), 135-167.

- Müller-Putz, G. R., Riedl, R., & C Wriessnegger, S. (2015). Electroencephalography (EEG) as a research tool in the information systems discipline: Foundations, measurement, and applications. *Communications of the Association for Information Systems*, 37, 911-948.
- Noesselt, T., Tyll, S., Boehler, C. N., Budinger, E., Heinze, H. J., & Driver, J. (2010). Sound-induced enhancement of low-intensity vision: multisensory influences on human sensory-specific cortices and thalamic bodies relate to perceptual enhancement of visual detection sensitivity. *Journal of Neuroscience*, 30(41), 13609-13623.
- Ortiz de Guinea, A., Titah, R., & Léger, P.-M. (2013). Measure for measure: A two study multi-trait multi-method investigation of construct validity in IS research. *Computers in Human Behavior*, 29(3), 833-844.
- Ortiz de Guinea, A., Titah, R., & Léger, P. M. (2014). Explicit and implicit antecedents of users' behavioral beliefs in information systems: A neuropsychological investigation. *Journal of Management Information Systems*, 30(4), 179-210.
- Pashler, H. (1994). Dual task interference in simple tasks: data and theory. *Psychological Bulletin*, 116(2), 220-244.
- Pauna, H., Léger, P. M., Sénécal, S., Fredette, M., Courtemanche, F., Chen, S. L., Labonté-Lemoyne, E., & Ménard, J. F. (2018). The psychophysiological effect of a vibro-kinetic movie experience: The case of the D-BOX movie seat. In F. Davis, R. Riedl, J. vom Brocke, P. M. Léger, & A. Randolph (Eds.), *Information systems and neuroscience* (LNISO vol. 25). Berlin: Springer.
- Paunonen, S. V., & Jackson, D. N. (2000). What is beyond the big five? plenty. *Journal of Personality*, 68(5), 821-835.
- Pelletier, C. L. (2004). The effect of music on decreasing arousal due to stress: A meta-analysis. *Journal of Music Therapy*, 41(3), 192-192.
- Penley, J. A., & Tomaka, J. (2002). Associations among the big five, emotional responses, and coping with acute stress. *Personality and individual differences*, 32(7), 1215-1228.
- Podsakoff, P. M., MacKenzie, S. B., Lee, J., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.
- Prensky, M. (2001). Digital natives, digital immigrants part 1. *On the Horizon*, 9(5), 1-6.
- Riedl, R. (2013). On the biology of technostress: Literature review and research agenda. *Database for Advances in Information Systems*, 44(1).
- Riedl, R., & Léger, P. M. (2016). *Fundamentals of neuroIS*. Berlin: Springer.
- Rosen, C. (2008). The myth of multitasking. *The New Atlantis*. Retrieved from <http://www.thenewatlantis.com/publications/the-myth-of-multitasking>
- Roy, P., Bérubé, M., & Jacques, M. (2003a). *Multi-sense home entertainment chair transducer system* (U.S. Patent No. 6,585,515). Washington, DC: U.S. Patent and Trademark Office.
- Roy, P., Bérubé, M., & Jacques, M. (2003b). *Motion transducer efficient for small amplitude movements* (U.S. Patent No. 6,662,560). Washington, DC: U.S. Patent and Trademark Office.
- Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, 110(1), 145-172.
- Ruthruff, E., Johnston, J. C., Van Selst, M., Whitsell, S., & Remington, R. (2003). Vanishing dual-task interference after practice: Has the bottleneck been eliminated or is it merely latent? *Journal of Experimental Psychology: Human Perception Performance*, 29(2), 280-289.
- Salomon, K. A., Ferraro, F. R., Petros, T., Bernhardt, K., & Rhyner, K. (2016). Individual differences in multitasking performance. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 60(1), 1255-1259.
- Sandler, H., Fendel, U., Buße, P., Rose, M., Bösel, R., & Klapp, B. F. (2017). Relaxation—induced by vibroacoustic stimulation via a body monochord and via relaxation music—is associated with a

- decrease in tonic electrodermal activity and an increase of the salivary cortisol level in patients with psychosomatic disorders. *PloS One*, 12(1), e0170411.
- Santangelo, V., Ho, C., & Spence, C. (2008). Capturing spatial attention with multisensory cues. *Psychonomic Bulletin & Review*, 15(2), 398-403.
- Schneider, T. R., Rench, T. A., Lyons, J. B., & Riffle, R. R. (2012). The influence of neuroticism, extraversion and openness on stress responses. *Stress and Health*, 28(2), 102-110.
- Srinivasan, R., Golomb, J. D., & Martinez, A. M. (2016). A neural basis of facial action recognition in humans. *Journal of Neuroscience*, 36(16), 4434-4442.
- Stephens, K. K. (2012). Multiple conversations during organizational meetings: Development of the multicommuting scale. *Management Communication Quarterly*, 26(2), 195-223.
- Strayer, D., & Watson, J. (2016). Top multitaskers help explain how brain juggles thoughts. *Scientific American*. Retrieved from <https://www.scientificamerican.com/article/test-your-multitasking-skills/>
- Stuijzand, S., De Wied, M., Kempes, M., van der Graaff, J., Branje, S., & Meeus, W. (2016). Gender differences in empathic sadness towards persons of the same- versus other-sex during adolescence. *Sex Roles*, 75(9-10), 434-446.
- Swickert, R. J., Rosentreter, C. J., Hittner, J. B., & Mushrush, J. E. (2002). Extraversion, social support processes, and stress. *Personality and Individual Differences*, 32(5), 877-891.
- Tams, S., Hill, K., Guinea, A., Thatcher, J., & Grover, V. (2014). NeuroIS—alternative or complement to existing methods? Illustrating the holistic effects of neuroscience and self-reported data in the context of technostress research. *Journal of the Association for Information Systems*, 15(10), 723-753.
- Tchanou, A. Q., Giroux, F., Léger, P. M., Senecal, S., & Ménard, J. F. (2018). Impact of information technology multitasking on hedonic experience. In *Proceedings of the Seventeenth Annual Pre-ICIS HCI/MIS Research Workshop Conference*.
- van Tilburg, Wijnand A. P., & Igou, E. R. (2012). On boredom: Lack of challenge and meaning as distinct boredom experiences. *Motivation and Emotion*, 36(2), 181-194.
- Terry, C. A., Mishra, P., & Roseth, C. J. (2016). Preference for multitasking, technological dependency, student metacognition, & pervasive technology use: An experimental intervention. *Computers in Human Behavior*, 65, 241-251.
- Wright, C. (2001). Children and technology: Issues, challenges, and opportunities. *Childhood Education*, 78(1), 37-41.
- Yang, Y.-H., Lin, Y.-C., Su, Y.-F., & Chen, H. H. (2008). A regression approach to music emotion recognition. *IEEE Transactions on Audio, Speech, and Language Processing*, 16(2), 448-457.
- Zhang, P. (2013). The affective response model: A theoretical framework of affective concepts and their relationships in the ICT context. *MIS Quarterly*, 37(1), 247-274.

Appendix A: Explicit Measures

Likert-type Questionnaires

Table A1. Self-reported Measures

Arousal (Ortiz de Guinea, Titah, & Léger, 2013, adopting measure from Deng & Poole, 2010)
<ul style="list-style-type: none"> • The music listening was stimulating • I felt excited during my activities on the company's mobile app and because of these activities • During the music listening, I felt jittery • The music listening made me be wide-awake
Valence
<ul style="list-style-type: none"> • My music listening experience was pleasant • My music listening experience was interesting • I had feelings of aversion during the music listening
Extraversion (Francis et al., 1992)
<ul style="list-style-type: none"> • Are you a talkative person? • Are you rather lively? • Do you enjoy meeting new people? • Can you usually let yourself go and enjoy yourself at a lively party? • Do you usually take the initiative in making new friends? • Can you easily get some life into a rather dull party? • Do you tend to keep in the background on social occasions? • Do you like mixing with people? • Do you like plenty of bustle and excitement around you? • Are you mostly quiet when you are with other people? • Do other people think of you as being very lively? • Can you get a party going?
Neuroticism (Francis et al., 1992)
<ul style="list-style-type: none"> • Does your mood often go up and down? • Do you ever feel "just miserable" for no reason? • Are you an irritable person? • Are your feelings easily hurt? • Do you often feel "fed-up"? • Would you call yourself a nervous person? • Are you a worrier? • Would you call yourself tense or 'highly strung'? • Do you worry too long after an embarrassing experience? • Do you suffer from 'nerves'? • Do you often feel lonely? • Are you often troubled about feelings of guilt?

Table A2. End-of-experiment Interview

<ul style="list-style-type: none"> • Would you have preferred experience the music listening on vibro-kinetic chair with closed eyes? • Would you like to live this experience again in the future? • Do you have other general comments?
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Appendix B: Assumptions of the Linear Model

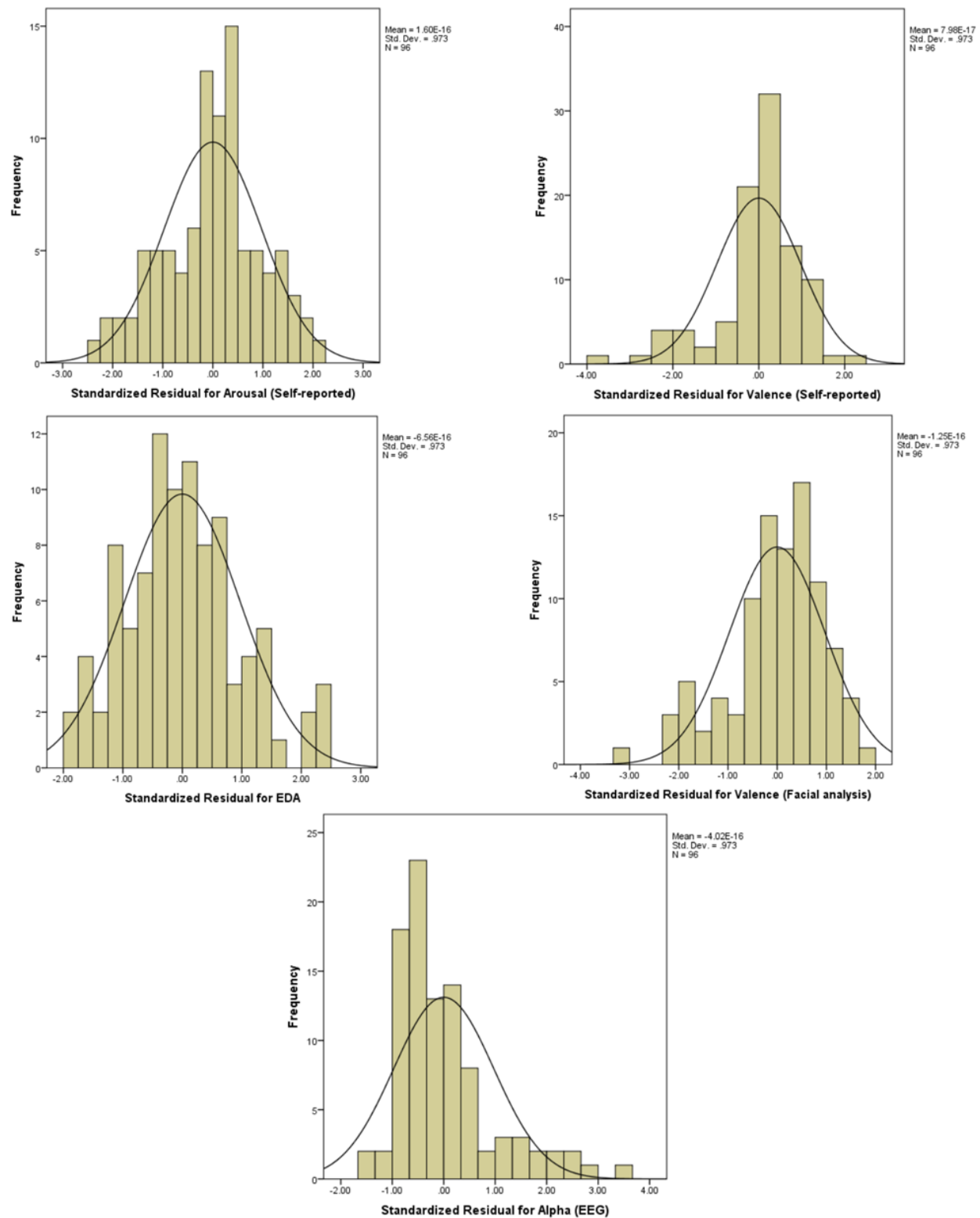


Figure B1. Normal Trend Of The Standardized Residual Plot

Appendix C: Summary Model Statistics for Analyses of Variance

Table C1. ANOVA Table for Self-reported Measures

Independent variables	Valence (self-reported)			Arousal (self-reported)		
	Mean square	F(1, 21)	p-value	Mean square	F(1, 21)	p-value
HFVKM	15.442	14.099	.0005***	2.608	1.488	.118
IT	.265	.369	.2250	.265	.369	.428
HFVKM*IT	8.076	6.439	.0095***	3.711	2.154	.079*
Error (HFVKM)	1.095			1.753		
Error (IT)	.717			1.711		
Error (HFVKM*IT)	1.254			1.723		

*** = significant at $\alpha = 0.01$; ** = significant at $\alpha = 0.05$; * = significant at $\alpha = 0.1$

Table C2. ANOVA Table for Self-reported Measures

Independent variables	Valence (facial analysis)			Arousal (EDA)		
	Mean square	F(1, 23)	p-value	Mean square	F(1, 23)	p-value
HFVKM	.368	5.435	.015**	.880	1.488	.118
IT	.017	.206	.327	.031	.152	.294
HFVKM*IT	.261	7.430	0.06*	.132	2.824	.053*
Error (HFVKM)	.068			.059		
Error (IT)	.082			.102		
Error (HFVKM*IT)	.035			.047		

*** = significant at $\alpha = 0.01$; ** = significant at $\alpha = 0.05$; * = significant at $\alpha = 0.1$

Appendix D: Three-way Interactions (Least Squared Means)

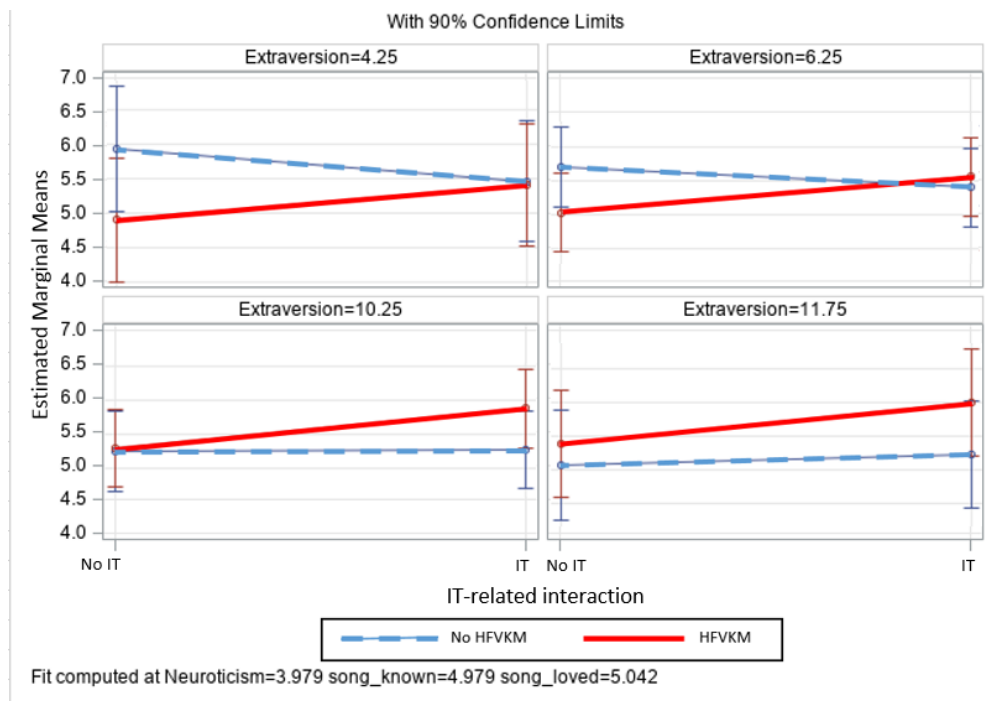


Figure D1. Fit for Valence (Self-reported)—Effect of Extraversion

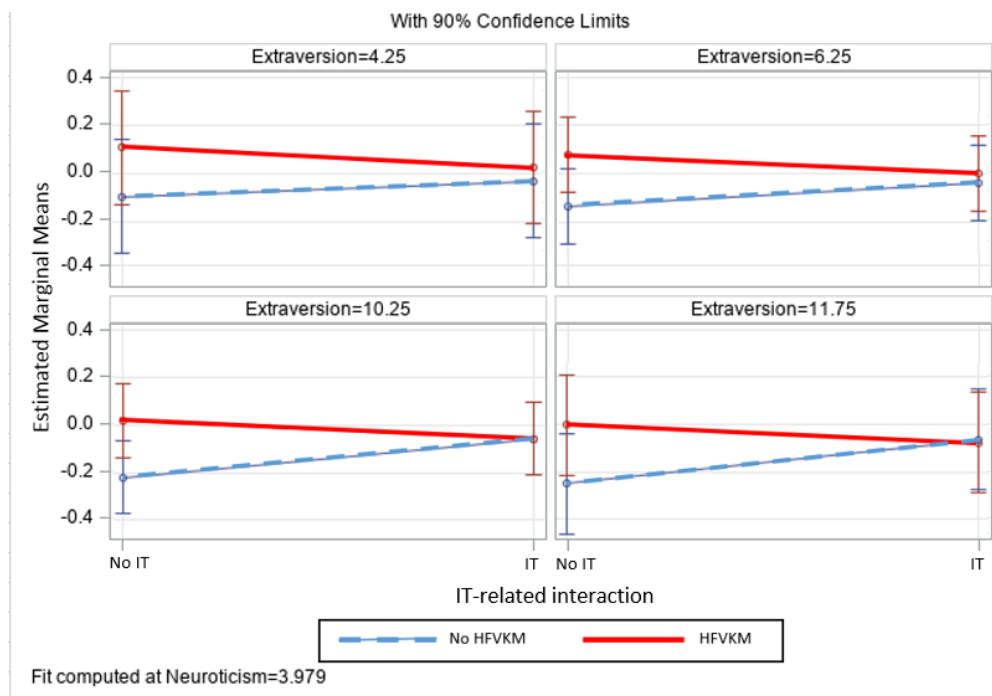


Figure D2. Fit for Valence (Facial Analysis)—Effect of Extraversion

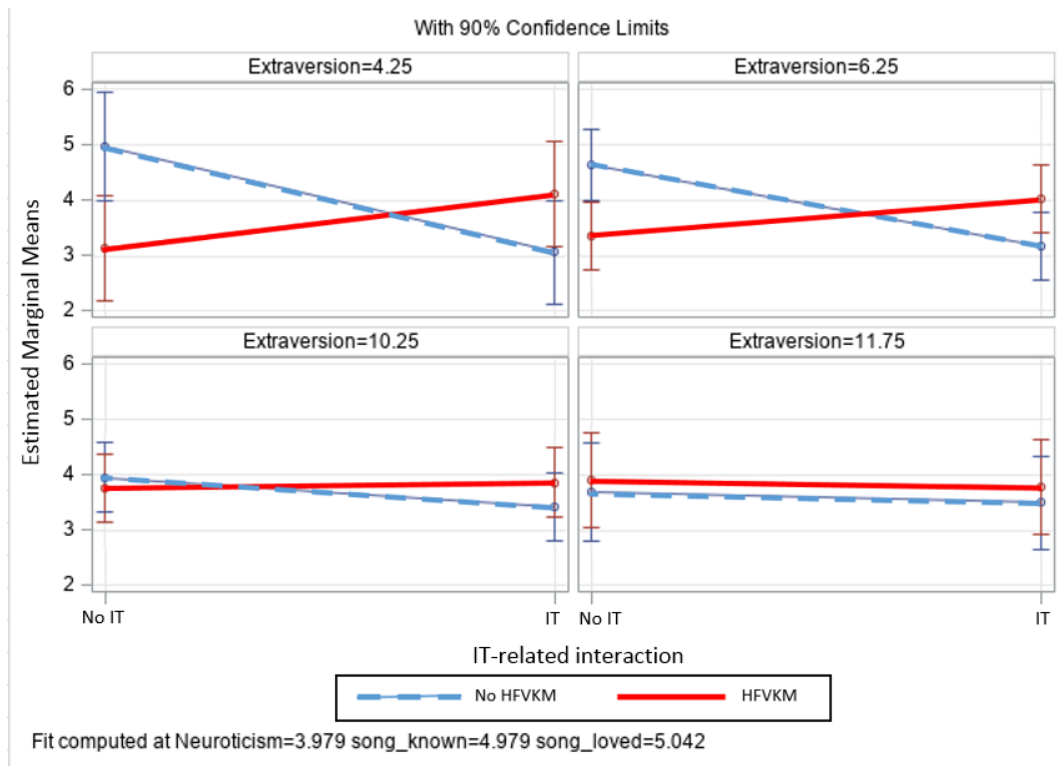


Figure D3. Fit for Arousal (Self-reported)—Effect of Extraversion

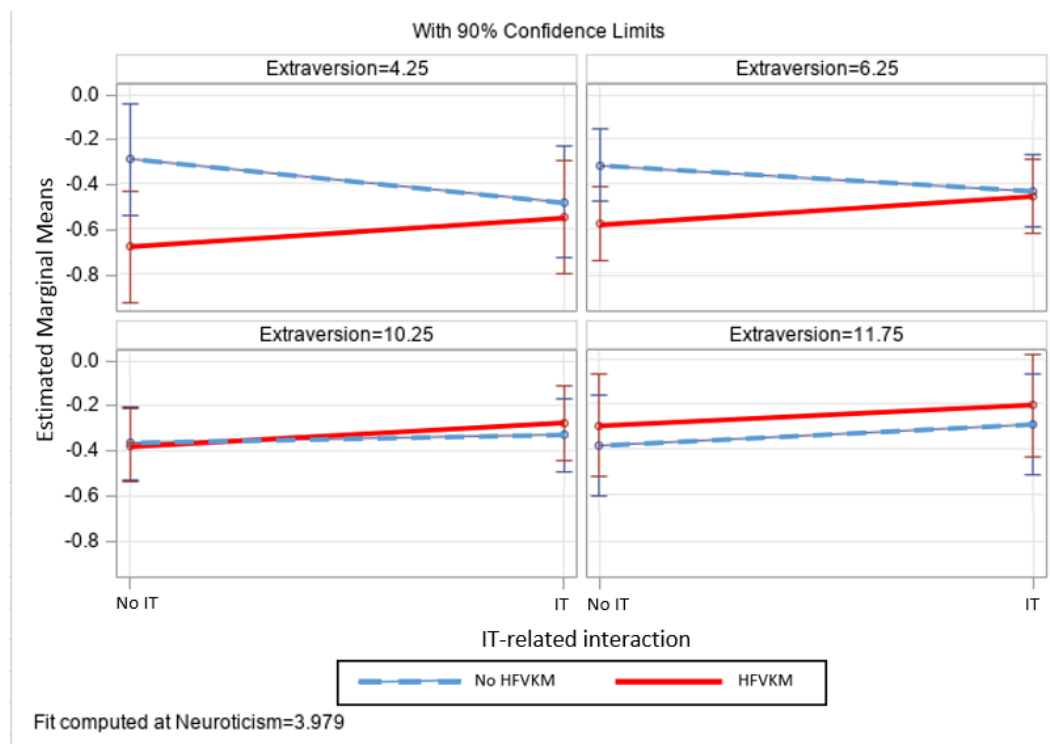


Figure D4. Fit for Arousal (EDA)—Effect of Extraversion

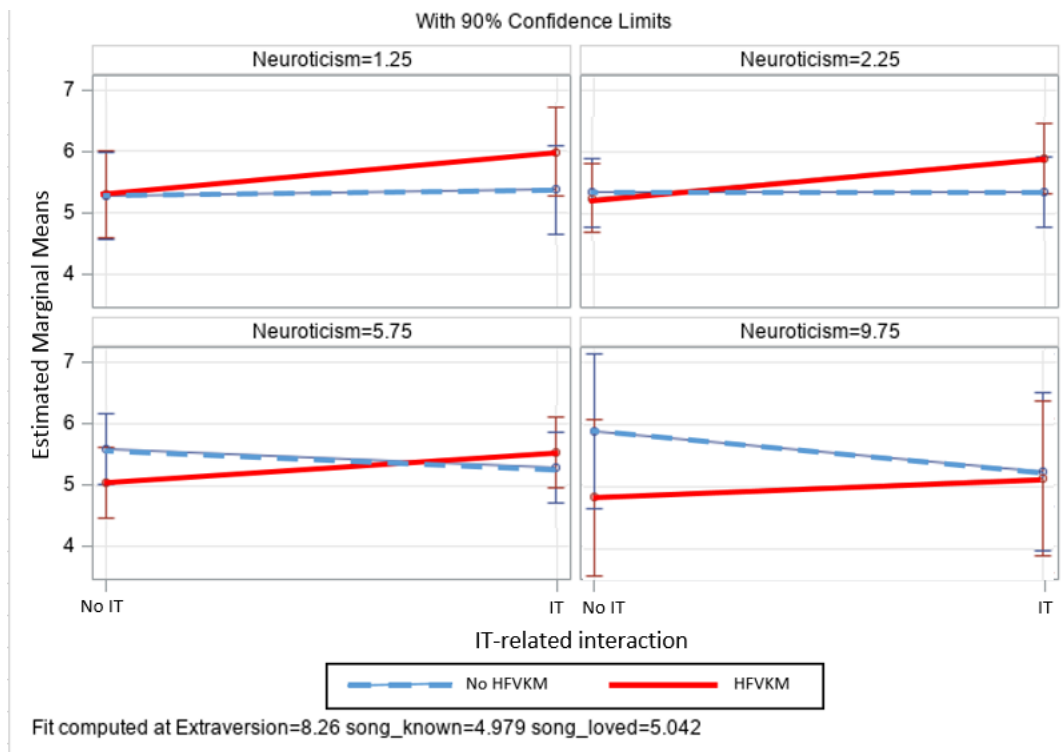


Figure D5. Fit for Valence (Self-reported)—Effect of Neuroticism

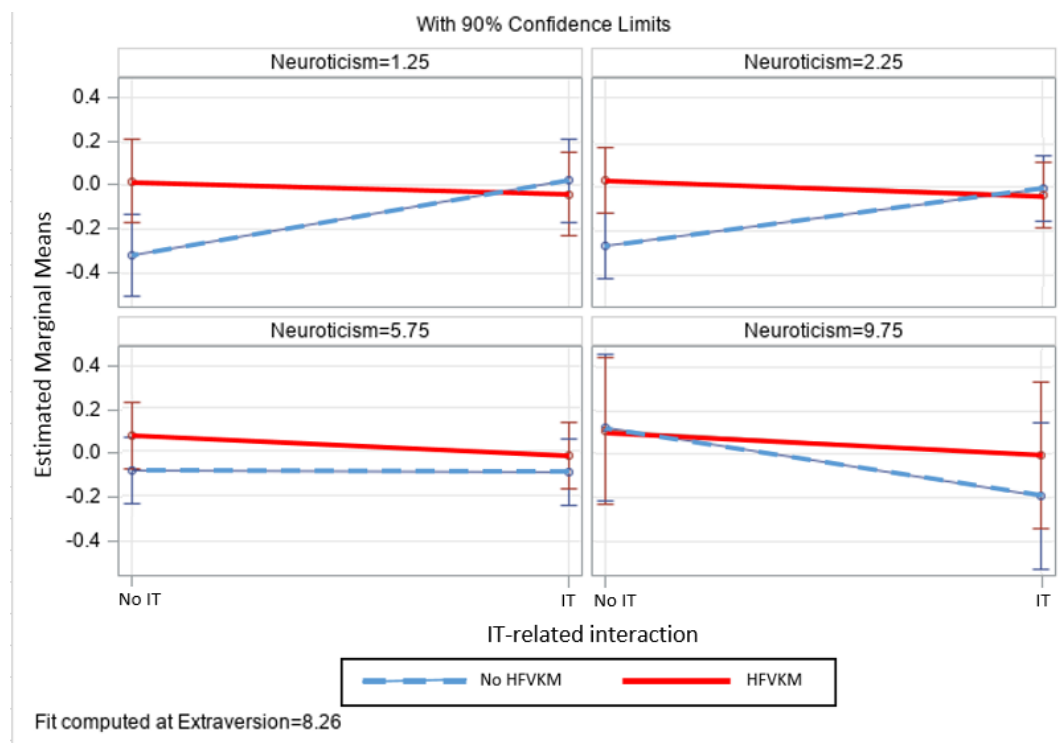


Figure D6. Fit for Valence (Facial Analysis)—Effect of Neuroticism

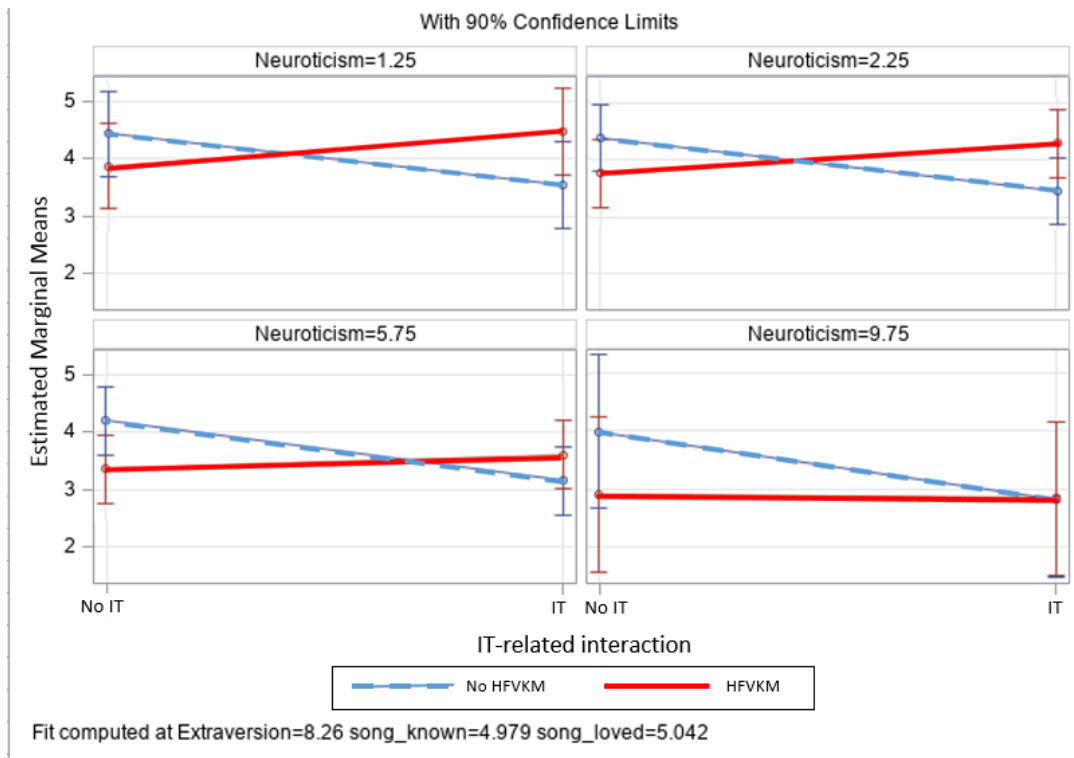


Figure D7. Fit for Arousal (Self-reported)—Effect of Neuroticism

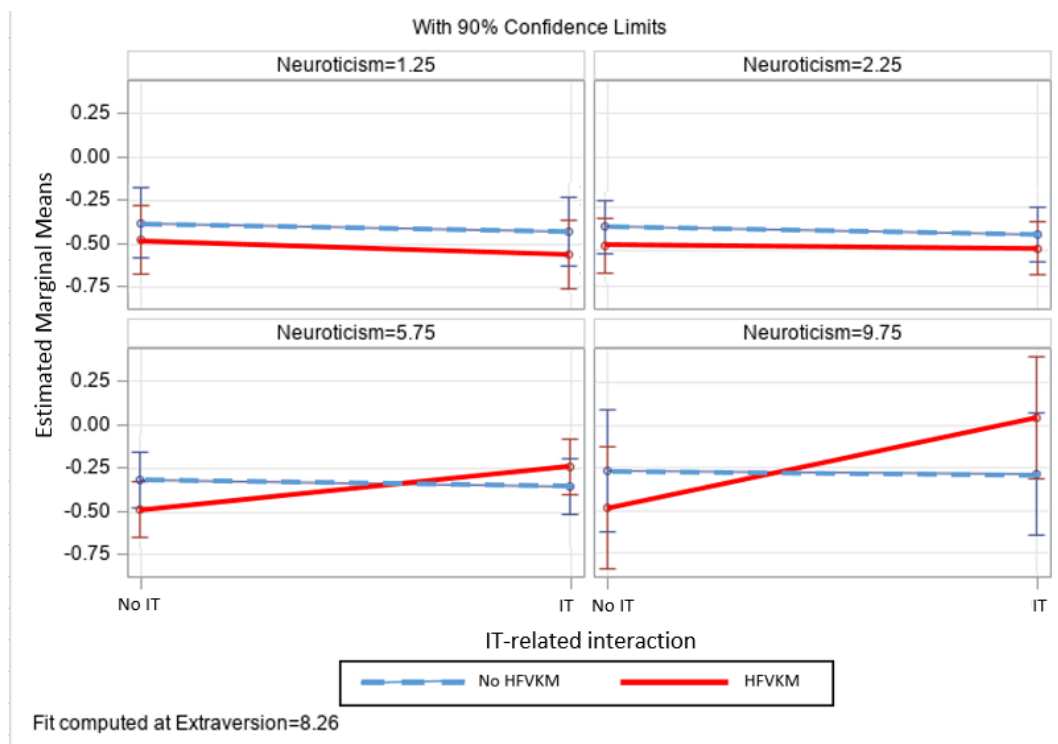


Figure D8. Fit for Arousal (EDA)—Effect of Neuroticism

Appendix E: Interview Results

Table E1. Interview Statistics

	“Yes” answers		“No” answers	
	Number	Percentage	Number	Percentage
Question 1 (would have liked closed eyes)	13	54.17%	11	45.83%
Question 2 (would like to live the experience again)	23	95.83%	1	4.17%

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