NOVA IMS Information Management School

MDDM

Master's Degree Program in

Data-Driven Marketing

WHAT IS THE INFLUENCE OF DIGITAL SELF-CONTROL TOOLS ON INDIVIDUAL PERFORMANCE?

Madalena Morais Machado Pereira Barreiros

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

WHAT IS THE INFLUENCE OF DIGITAL SELF-CONTROL TOOLS ON INDIVIDUAL PERFORMANCE?

by

Madalena Morais Machado Pereira Barreiros

Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Digital Marketing and Analytics

Supervised by

Tiago Oliveira, PhD, NOVA Information Management School

February, 2024

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

[Lisbon, 29th February]

DEDICATION

I dedicate this thesis to my parents and sister for their unconditional support and constant encouragement. Their belief in me has been a driving force behind my accomplishments. Additionally, I dedicate this work to my boyfriend, whose motivation and belief in me fueled my determination to reach this milestone.
Thank you for standing by my side through it all.

ABSTRACT

Research about digital self-control tools is in its infancy. As a result, their effectiveness and impact on user behaviour remain to be understood. This research will fill this gap by analysing the determinants of digital self-control tools that influence individual performance. To do so, we proposed a research model which combines Goodhue & Thompson's (1995) task-technology fit (TTF) model with other constructs such as self-control, technology addiction, motivation, continuance intention and severity of enforcement. Thus, we administered an online survey to 212 respondents. Our findings suggested that technology characteristics and self-control positively affected TTF, and, therefore, TTF influenced the utilization of DSCTs. Furthermore, our results highlighted the mediating role of motivation in the relationship between the utilization of DSCTs and the perceived TTF of the users. Lastly, the moderators' technology addiction and severity of enforcement demonstrated significant effects on individual performance over utilization.

KEYWORDS

Digital Self-Control Tools; Digital Wellbeing; Individual Performance; Task-Technology Fit;

Sustainable Development Goals (SDG):

3 GOOD HEALTH AND WELL-BEING

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

DSCTs	Digital Self-Control Tools
ACDPs	Attention-Capture Damaging Patterns
IT	Information Technology
TTF	Task-Technology Fit

1. INTRODUCTION

In defiance of the ubiquitous connectivity offered by digital technologies, an extensive body of research outlines the struggle individuals face to resist the temptations of digital devices, thus falling victim to excessive use of these means (Monge Roffarello & De Russis, 2023a). Moreover, many people feel conflicted about the time spent on digital technologies, mainly when such use appears void of purpose and passive (Lukoff et al., 2018).

Consequently, promoting individuals' digital well-being stands out as one of the most urgent challenges in today's society (Monge Roffarello & De Russis, 2023c). Researchers have recognized that technology can also be part of the solution for aiding users in regulating their digital usage, improving their relationship with these means, tackling its adverse effects, and fostering digital well-being. A promising approach to address this challenge involves adopting digital self-control tools (DSCTs). Schwartz (2019) defines DSCTs as self-restraint applications that limit future use of specific applications, groups of applications or the device itself, contributing to regulating user behavior with digital means. Remarkably, an entire niche market has developed in Android and Apple stores, in addition to the numerous browser extensions designed for those struggling with digital self-control (Lyngs et al., 2019).

While earlier research has focused on comprehending and analyzing the functionalities and effectiveness of these interventions, the impact on user behavior still needs to be understood. Moreover, the research about DSCTs lacks a comprehensive theoretical foundation, with considerable studies not relying on any behavioral theories nor providing enough evidence on how acknowledged theories relate to these interventions (Hekler et al., 2013). Our approach focuses on filling this gap by analyzing the impact of digital self-control tools on individual performance. Our research question is: “What influences the individual performance of digital self-control tools?” To do so, we propose a research model which combines Goodhue & Thompson's (1995) task-technology fit model with other constructs such as self-control, technology addiction, motivation, continuance intention and severity of enforcement.

2. LITERATURE REVIEW

2.1. TECHNOLOGY ADDICTION

Smartphones, laptops, and tablets have become integral to our work, social and leisure lives. These technologies allow us to connect to people, services and content without time or place constraints (Vanden Abeele, 2021). In January 2023, the global internet user base reached 5.16 billion users worldwide, which corresponded to 64.4 percent of the global population. As of the first quarter of 2023, internet users spent an average of six hours and forty minutes online daily (Petrosyan, 2023). This data proves that digital technology is transforming individuals and reshaping societal interactions, leveraging vast online information and communication platforms (Small, 2020).

Despite the ubiquitous connectivity provided by digital technologies, the passive consumption of digital content has raised many questions about the time spent on digital devices (Roffarello & De Russis, 2022). Nowadays, there is an increasing recognition of the "dark sides" of digital technology, which may harm individual and societal dynamics (Turel et al., 2021). As a result, a growing amount of public discourse and research attention centers on technology addiction. Technology addiction is an emerging behavioral addiction that results from the excessive and uncontrollable use of technologies, indispensable tools of everyday life (Sherer & Levounis, 2022). Research shows that technology addiction is significantly associated with depression, anxiety, sleep disorders and poor mental health (Jamir et al., 2019). Reports also revealed that technology addiction negatively affected productivity in the workplace and individuals' daily tasks (Madlock & Hessling, 2020)

Griffiths (2018) states that technology addiction can be diagnosed by six core symptoms: salience, mood modification, tolerance, withdrawal, conflict and relapse. Salience implies a progressive increase in technology use, dominating one's thoughts and actions. This addictive behavior conflicts with other activities such as social life, work and familial responsibilities. As a result of this addictive behavior, one must experience mood modification, that is, excitement or relief when using the technology despite being aware of the harm caused. Tolerance means longer and higher-intensity behavioral sessions are necessary to maintain one's mental state. Furthermore, one must face withdrawal, intense emotional and physical discomfort when the use discontinues. Lastly, a person can try to reduce or cease the addictive behaviors but relapses, and levels of behavior increase after abstinence periods.

According to Serenko and Turel (2020), users are not addicted to an IT artefact. Instead, they get addicted to a behavior mediated by an IT artefact. While technological artefacts are non-addictive, that does not absolve responsibility from software developers and providers, who induce addictive tendencies with triggers such as notifications, interruptions, feature-rich IT, hedonic features, and personalized and changing content (Kloker, 2020). Complementarily, Monge Roffarello et al. (2023) introduce the concept of Attention-Capture Damaging Patterns (ACDPs), deceptive functionalities that incite users to perform activities not aligned with their best interests. Additionally, Cho et al. (2021) state that ACDPs have three core characteristics: they distract a person from a determined goal and, therefore, compromise the individual autonomy; they lead a person to feel lost in control and time; and they induce a person to experience regret about the time spent on a determined service. ACDPs can be found in various formats, for instance, Infinite Scroll, Auto-Play, or Pull-to-refresh design patterns, which persuade users to participate in passive consumption. Such features can foster addiction by providing rewards and suppressing components that stimulate self-control, leading users to consume content subconsciously and struggle to exert self-control over device use (Serenko & Turel, 2020).

2.2. SELF-CONTROL

Self-control relates to the self's ability to revoke or alter one's inner responses in addiction to interrupt unwanted behaviors and abstain from acting on them, playing a vital role in achieving valued goals and embodying the conscious and deliberate elements of self-regulation (Baumeister et al., 2007). According to Kotabe and Hofmann (2015), self-control comprises three components: a desire, a higher objective and an intrinsic conflict that arises between the two. Individuals can encounter conflicts between two distal valued objectives or two near desires. However, significant self-control-related cognitive disruption occurs when a desire is discordant with a distal objective. Therefore, self-control implies a conflict between a desire and a distal objective (Taylor et al., 2018).

Research by Nilsen et al. (2020) highlights that self-control is a fundamental trait that shapes the core of an individual's personality as it develops, beginning in the early stages of life and stabilizing over different circumstances and periods. However, self-control capacity is limited, and exertion can drain its strength. According to the Strength Model of Self-Control, self-control resembles a muscle that faces exhaustion and becomes less able to function as it faces subsequent efforts (Baumeister et al., 2007). Hence, there are substantial disparities in individuals' levels of trait self-control, with individuals with higher self-control benefiting from positive emotional and social effects. Moreover, higher levels of self-control correlated with higher self-esteem, interpersonal skills, and more optimal emotional responses (Tangney et al., 2004). Additionally, high self-control scores anticipate excellent work performance, relationship fulfilment, well-being effects and perceived meaning of life (Li et al., 2021).

In contrast, a deficit in self-control scores correlates with impulsiveness, risk-taking and addictions such as substance, games, social media and technology addiction (Cudo et al., 2019). Previous studies pointed out that exercising self-control reduces technology addiction. For instance, Gökalp et al. (2022) found that self-control was negatively linked to multi-screen addiction, meaning that lower levels of self-control are associated with higher levels of multi-screen addiction. Moreover, Li et al. (2021) study shows that self-control has a negative association with Internet addiction, denoting that individuals with higher self-control scores were less likely to engage in behaviors that promoted internet addiction and were more likely to make short-term sacrifices for long-term goals. In addition, Kwak et al. (2022) report that enhancing trait self-control may protect individuals from developing addictive smartphone usage.

2.3. DIGITAL SELF-CONTROL TOOLS

Research indicates that many individuals are incapable of resisting the temptations of digital technologies, hence experiencing difficulties controlling device usage and often falling victim to compulsive actions such as scrolling social media newsfeeds (Monge Roffarello & De Russis, 2023a). These findings have recently led researchers to contemplate a new form of psychological well-being affecting current society: digital well-being (Monge Roffarello & De Russis, 2022).

Vanden Abeele (2020) defines Digital Well-being as individuals' capacity to find an optimal balance between the benefits and disadvantages of connectivity. According to the author, individuals achieve digital well-being when they experience maximal controlled pleasure and practical support without losing control and causing functional damage. Device manufacturers have already included digital well-being tools in their operating systems, despite their demand for the opposite, recognizing online compulsive behaviors as a severe problem (Thomas et al., 2022). Furthermore, Monge Roffarello and De Russis (2023c) state that contributing to an individual's digital well-being is one of the most critical challenges in current society.

According to Lyngs et al. (2019), exercising self-control must be the focus of effectively achieving digital well-being. Thus arises the term Digital Self-Control Tools (DSCTs). DSCTs can be defined as self-restraint applications that limit future use of specific applications, groups of applications or the device itself, contributing to regulating user behavior with digital means (Schwarts, 2019). As a result, an entire niche market has developed in Android and Apple stores, in addition to the numerous browser extensions designed for those struggling with digital self-control (Lyngs et al., 2019).

Lyngs (2019) conducted exploratory research to uncover the main features of digital self-control tools. Therefore, clustered DSCTs functionalities into four types: block or removal (features that hinder distractions, for instance, momentarily locking user’s access to specific apps or hide them, for example, suppressing recommended videos on YouTube); self-tracking (features which allow monitoring and viewing applications or device usage); goal-advancement (features that recall user’s usage goals including, displaying a notification when a determined amount of time has passed) and reward/punishment (features which provide recompenses for using devices in specific ways).

In a recent study, Monge Roffarello and De Russis (2022) delved further into DSCTs, expanding Lyngs’ categorization. Their research identified seven additional features that have become popular to the landscape of digital self-control tools: auto close (features that automatically closes applications or websites following a determined time interval); delay (features which employ delay of gratification components for instance, compel user's to solve a task before accessing an app or website); modification (features that adjust websites aspects that are somewhat distracting); gamification (features which apply game-like components to captivate users in less distracting behaviors); pomodoro (features that prompts the use of pomodoro method, where the users determine a period that is reserved for focused tasks after which they are authorized to take a break); compare (features which allows users to share and compare their improvement in controlling device or applications usage, fostering users to stay engaged); screenshare (features that provides users the possibility to create learning groups and track each other's device or application usage).

Research about digital self-control tools is in its infancy. According to Monge Roffarelo and De Russis (2022), prior research about DSCTs has focused on understanding and analyzing the functionalities of these interventions that aim to improve digital well-being. As a result, their effectiveness and impact on user behavior remain to be addressed. Moreover, Hekler et al. (2013) argue that previous literature about DSCTs lacks a comprehensive theoretical foundation, with considerable studies not relying on any behavioral theories nor providing enough evidence on how acknowledged theories relate to these interventions (Hekler et al., 2013).

This research will focus on filling this gap by analyzing the impact of digital self-control tools on individual performance as it delves into a novel topic in this field. To do so, the Task-Technology Fit model (Goodhue & Thompson, 1995), which arises from the information systems field, will serve as the foundational framework for our research.

2.4. TASK-TECHNOLOGY FIT

In 1995, Goodhue and Thompson introduced the task-technology fit (TTF) model, founded on the premise that the effectiveness of technology depends on its fit or alignment with the tasks it intends to support. According to Spies et al. (2020), TTF is a theoretical framework that measures how technology enhances performance. Nevertheless, recent studies have used TTF to forecast the acceptance and usage of the latest technology (Vanduhe et al., 2020). The model has been used in a variety of technological contexts, such as video conferencing applications (Alturki & Aldraiweesh, 2022), mobile health apps (Zaidi et al., 2020) and social networking applications (Alamri et al., 2020). However, studies on DSCTs have yet to explore the potential of TTF.

The basic TTF model comprises four constructs: task characteristics, technology characteristics, task-technology fit and performance impacts (Lin et al., 2020). Task characteristics denote individuals' actions in turning inputs into outputs (Goodhue & Thompson, 1995). According to Tam & Oliveira (2019), these characteristics can differ in various dimensions, such as task unrepeated ness, task interdependence, and time criticality. In the context of DSCTs, we can assume that if DSCTs functionalities match the user's tasks to be executed, the task performance will increase.

On the other hand, technology characteristics reference the tools individuals employ in executing their tasks (Goodhue & Thompson, 1995). For example, DSCTs allow users to perform their tasks better by blocking apps or hiding distracting websites, tracking, and visualizing the usage of technological devices or particular applications and providing rewards or punishments depending on how devices are employed (Lyngs et al., 2022). Hence, task-technology fit can be defined as the extent to which a determined technology aids an individual in efficiently and effectively executing their tasks.

Moreover, Howard Rose (2018) suggests that TTF moderates the effects of task and technology characteristics on technology use and performance outcomes. A performance impact translates into the outcome of employing technology to execute a portfolio of tasks. Additionally, Goodhue and Thompson (1995) argue that utilization represents the behavior of exerting a determined technology to perform tasks. Therefore, the TTF model supposes that users are rational and will continue to use the technology as long as it best supports the task they wish to perform (Tam & Oliveira, 2016).

3. RESEARCH MODEL

Based on the scholarly literature and the theories mentioned above, we propose a research model to study the influence of DSCTs on individual performance. The model comprises ten constructs: task characteristics, technology characteristics, task-technology fit, utilization, individual performance, self-control, technology addiction, motivation, continuance intention and severity of enforcement.

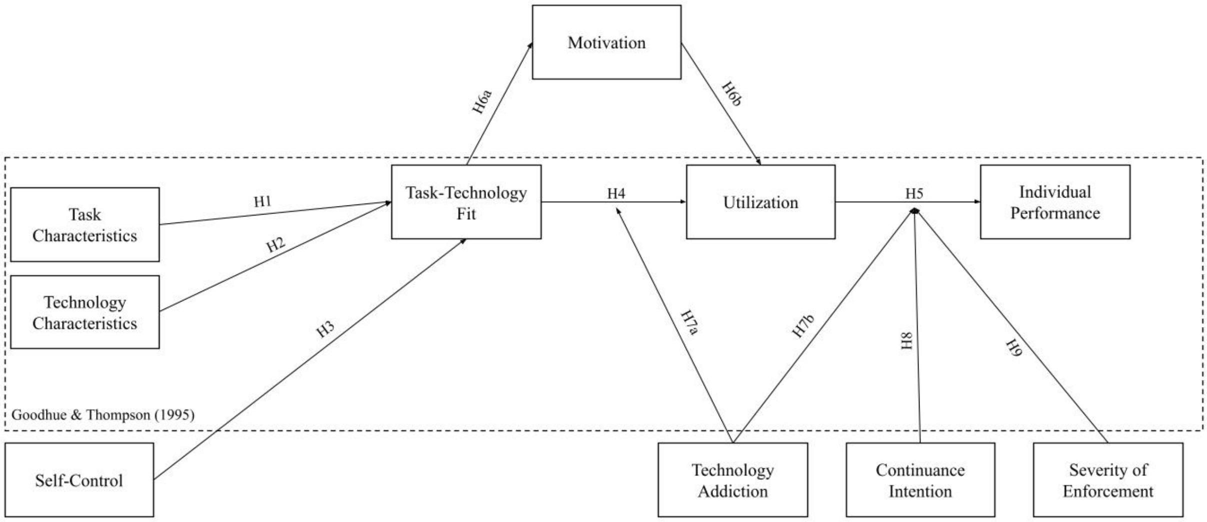

Figure 1 – Research Model

From the TTF perspective, task characteristics are actions users execute when employing DSCTs (Goodhue & Thompson, 1995). According to Lyngs' (2019) study, which analyzed ratings and reviews regarding demanded digital self-control applications, the main tasks requested by users are enhancing focus on relevant but effortful tasks, improving time management, and controlling device overuse. Thus, we suggest the following hypothesis:

H1 - Task characteristics of DSCTs users positively affect task-technology fit.

Technology characteristics are physical and logical tools individuals employ in executing their tasks (Franque et al., 2022). For instance, DSCTs empower users to improve task performance by blocking apps or hiding distracting websites, tracking, and visualizing the usage of technological devices or applications and providing rewards or punishments depending on how devices are employed (Lyngs., 2019). Therefore, we hypothesize:

H2 - Technology characteristics of DSCTs positively affect task-technology fit.

In the context of TTF, individual traits can influence the easiness and effectiveness of an individual using a determined technology (Goodhue & Thompson, 1995). This study focuses on one specific individual characteristic: self-control. Self-control refers to the self's ability to revoke or alter one's inner responses in addiction to interrupt unwanted behaviours and abstain from acting on them (Cheung et al., 2014). Consequently, we hypothesize:

H3 – Trait self-control of DSCTs users positively affect task-technology fit.

Goodhue and Thompson (1995) describe task-technology fit as the degree to which technology aids a user in executing his tasks and is, consequently, influenced by the fit between task and technology characteristics. Hence, when DSCTs' users recognize a high degree of match between the tasks they aim to execute and the technology, the usage of DSCTs is most likely to improve. In contrast, a lower degree of fit decreases user intention to adopt DSCTs. For this reason, we suggest the following hypothesis:

H4 - Task-technology fit positively affects the utilization of DSCTs.

As claimed by Franque et al. (2022), when users start to utilize any system, they begin to perceive advantages. This holds true for DSCTs as well. When using DSCTs, users will recognize its benefits, and the level of perceived individual performance will increase. According to Lyngs et al. (2022), DSCTs are particularly useful for individuals who aim to focus on significantly delayed rewards when digital distractions arise, particularly in contexts associated with productivity. So, we hypothesize:

H5 - The utilization of DSCTs positively affects individual performance.

The mediating role of motivation

A significant barrier DSCTs users encounter is the decline in motivation levels over time, potentially resulting in the discontinuation of DSCTs. Recent findings suggest that DSCTs users cease the use of these tools due to their decreased motivation and sense of laziness (Biedermann et al., 2023). Building on this observation, we hypothesize:

H6a - Task-technology fit positively mediates the motivation of DSCTs' users who perceive greater task-technology fit present higher motivation levels regarding the use DSCTs.

H6b – Motivation positively mediates the utilization of DSCTs so that users are more likely to engage with and withdraw benefits from these tools if they demonstrate a high level of motivation.

The moderating role of technology addiction

According to Roffarello and De Russis (2022), the main driver for individuals using DSCTs is their difficulty in practicing self-control over digital usage, negatively affecting their subjective well-being. Moreover, findings from Lyngs et al. (2022) suggest that DSCTs are exceptionally functional for users who self-identify as "addicts'' or are struggling significantly with distractions. Consequently, we hypothesize:

H7a - Technology addiction positively moderates the utilization of DSCTs so individuals dealing with technology addiction will be more prone to utilize these tools.

H7b - Technology addiction positively moderates individual performance so that technology addicts perceive higher individual performance when employing DSCTs.

The moderating role of continuance intention

In literature, the scarcity of motivation has implications for the continuance intention to use DSCTs, thereby exerting influence on the effectiveness of these tools. As mentioned by Biedermann et al. (2023), DSCTs use oscillates, reaching their peak during stressful times and decreasing during more ease periods. Complementarity, Lyngs et al. (2022) argue that DSCTs, in many instances, are employed to aid individuals with defined and unpleasant tasks. Consequently, when the use of DSCTs is infrequent and seasonal, the prospect of consolidating enduring behavior change or cultivating new beneficial habits is lower (Biedermann et al., 2023). For this reason, we suggest the following hypothesis:

H8 - Continuance intention positively moderates individual performance since DSCTs' users benefit from higher individual performance when they maintain their continuance intention at a stable level.

The moderating role of severity of enforcement

Another factor which researchers have investigated is the severity of the enforcement and the degree of friction within DSCTs (Lukoff et al., 2022). According to the authors, users tolerate weak enforcement very well in DSCTs. However, original objectives are easily and often bypassed. On the other hand, strict enforcement is more effective in helping users achieve their goals, yet it can trigger frustration and conduct to disuse them too. Hence, DSCTs must offer a medium level of enforcement to increase adherence and retain users. For this reason, we suggest the following hypothesis:

H9 - The severity of the enforcement positively moderates individual performance since users benefit from higher individual performance when DSCTs offer a moderate level of enforcement.

4. METHODS

4.1. MEASUREMENT

An online questionnaire was developed to collect data for the analysis. To measure each construct of this model, the survey items that composed the questionnaire were derived from scholarly literature and were adapted to be consistent with the topic of this study. The items for all constructs that comprised the questionnaire and their corresponding references are listed in Appendix A. Moreover, the items were measured using a seven-point range scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

4.2. DATA COLLECTION

The survey was designed and administered in English using Qualtrics. Initially, a pilot questionnaire was conducted to ensure the validity and reliability of all measurement items. The results did not indicate any issues; therefore, further refining the questionnaire was unnecessary.

The survey was distributed online, and the data collection phase lasted between November 2023 and January 2024, during which 212 valid responses were obtained.

Before the start of the questionnaire, a comprehensive introduction was presented to the participants, providing them with a clear understanding of the concept of DSCTs and their main features to ensure that the respondents had a solid understanding of the topic and could provide informed and accurate responses to the questions presented.

Regarding the sample's demographic characteristics, an equal proportion of the respondents (48%) identified as male and female, while 4% identified as non-binary. The sample in question was predominantly composed of individuals under the age of 25 (50%), and 31% of the participants were between the ages of 25 and 34. As for the education levels of the sample, 69% of the respondents were academic graduates holding degrees at the bachelor's, master's or doctoral level.

Moreover, a significant part of the sample, 60%, reported using DSCTs. Among these participants, usage patterns varied, with 21% affirming occasional use, 28% stating sometimes usage and 24% revealing frequent usage. These findings were expected, consistent with the fact that DSCTs are still in the early stages of development. Comprehensive descriptive statistics regarding the characteristics of the respondents are presented in Table 1.

Table 1 – Sample characteristics

Distribution (n=212)					
Gender			**Use of DSCTs**		
Male	102	48%	Yes	127	60%
Female	102	48%	No	85	40%
Non-binary	8	4%			
Age			**DSCTs usage frequency**		
<25	106	50%	Never	0	0%
25-34	66	31%	Rarely	8	6%
35-44	21	10%	Occasionally	26	21%
>44	19	9%	Sometimes	35	28%
			Frequently	31	24%
			Usually	17	13%
			Everytime	10	8%
Education					
High School	66	31%			
Bachelor’s degree	95	45%			
Master’s degree or higher	51	24%			

5. RESULTS

The data analysis was founded on a widely accepted method in social sciences, designated partial least squares structural equation modelling (PLS-SEM), which enables the calculation of path models with latent variables and their respective relationships. Moreover, PLS-SEM can evaluate complex models comprising various constructs and indicator variables based on small-sized samples (Sarstedt et al., 2021).

Considering this method suitable for the present context, we relied on Smart PLS, a recognized software application for variance-based structural equation modelling (SEM) employing the partial least squares (PLS) path modelling. In the first instance, the measurement model was evaluated to determine its reliability and validity. Subsequently, the structural model was examined.

5.1. MEASUREMENT MODEL

During this step, the reliability, convergent and discriminant validity of the constructs comprising the research model were evaluated. It was imperative to consider Cronbach's Alpha (CA) and Composite Reliability (CR) to assess the model's reliability. Hair et al. (2021) state that the interpretation for CA and CR is consistent: values between 0.60 and 0.70 are deemed acceptable in exploratory research, while those between 0.70 and 0.90 vary from satisfactory to good.

Upon reviewing the values in Appendix C, it is evident that most of the constructs exhibit highly satisfactory reliability, with CA and CR value exceeding 0.8. However, three constructs, self-control, utilization, technology characteristics, indicate satisfactory levels of reliability with both CA and CR values above 0.7. It is also worth mentioning that the construct, task characteristics, has a relatively lower CA value (0.609). Nevertheless, based on the CR value (0.814), the construct demonstrates good reliability, implying internal consistency despite the lower CA value.

Subsequently, an analysis of the convergent validity of the constructs was conducted. Hair et al. (2021) assert that the average variance extracted (AVE) measures the construct's convergent validation. According to the authors, the minimum acceptable value for AVE is 0.50, meaning that the latent variables justify at least 50% of the variance of the indicators. Reviewing the values in Appendix C revealed that the AVE for each construct exceeds 0.5, thus confirming convergent validity.

To assess the model's discriminant validity, the traditional measure of the Fornell-Larcker Criterion can be employed. In this case the discriminant validity is verified for each pair of latent variables if the AVE for both variables exceeds their squared correlation (Fornell & Larcker, 1981). However, recent studies, such as Hair et al. (2021), suggest that this metric may not be the most suitable for discriminant validity assessment. Instead, researchers can rely on the heterotrait-monotrait (HTMT) measure as a more robust alternative. The HTMT values of all the constructs were below the threshold value of 0.9.

The cross-loadings of the constructs comprising the research model were also evaluated. As shown in Appendix B, the loadings of each indicator on its corresponding construct are greater than the cross-loadings on other constructs.

In sum, the proposed model for this research exhibits strong reliability, convergent validity, and discriminant validity, providing a solid foundation for further analysis of the structural model.

5.2. STRUCTURAL MODEL

Once the constructs' reliability and validity are confirmed, the subsequent step involves evaluating the outcomes of the structural model results. This process implies examining the strength and significance of the paths connecting the various constructs within the research framework (Hair, Hult, et al., 2021). As emphasized by the authors, it is imperative to test the multicollinearity of all constructs using the variance inflation factor (VIF), ensuring that these remain below 5. The VIF values for the constructs within our model ranged from 1.000 to 3.526, revealing the inexistence of multicollinearity issues, which allowed us to proceed confidently with interpreting the results. To do so, we applied the bootstrapping technique to estimate the significance of the path coefficients using t-values (Hair, Hult, et al., 2021).

Figure 2 presents the structural model and includes the R-squared and the path coefficients resulting from bootstrapping 5000 samples.

TTF explains 50.2% of the variation within the model. However, the analysis reveals that task characteristics (β = 0.094, p = 0.188) does not demonstrate statistical significance in explaining TTF, hence failing to support H1. In contrast, technology characteristics (β = 0.633, p = 0.000) and self-control (β = 0.139, p = 0.041) both reveal statistically significant in defining TTF, thus corroborating H2 and H3.

Moreover, the utilization of digital self-control tools justifies 43.3% of the variance explained by TTF (β = 0.283, p = 0.002), thereby supporting H4.

Regarding individual performance, it accounts for 52.7% of the model's variance. Nevertheless, the analysis suggests that utilization (β = 0.501, p = 0.000) reaches statistical significance in explaining individual performance, hence confirming H5.

Additionally, the motivation of digital self-control users sustains 39.9% of the model's variance. Both TTF (β = 0.632, p = 0.000) and utilization (β = 0.398, p = 0.000) have a statistically significant effect on motivation, supporting H6a and H6b.

The subsequent hypotheses represent moderating variables. Notably, technology addiction (β = 0.141, p = 0.035) and severity of enforcement (β = -0.141, p = 0.045) emerge as statistically significant, thereby confirming H7b and H9. However, the negative coefficient for H9 suggests that the severity of enforcement weakens the relationship between utilization and individual performance when employing digital self-control tools.

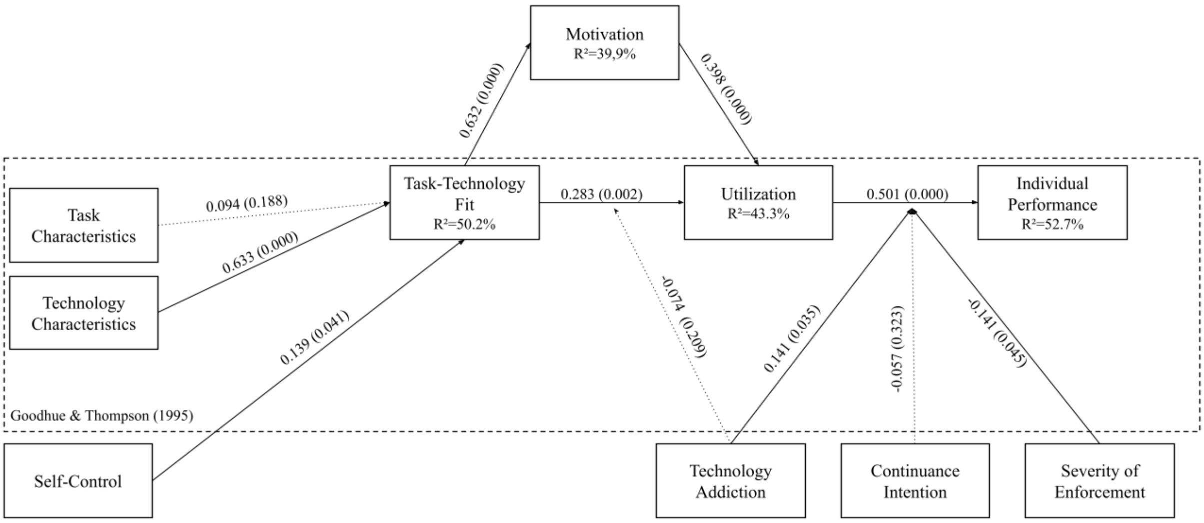

Figure 2 – Results of Research Model

According to Sarstedt et al. (2020), a variable represents a mediator if it intercedes between two related constructs. Therefore, changes in the independent construct led to alterations in the mediator variable, subsequently influencing changes in the dependent construct. The results of the mediation analysis are detailed in Table 2.

From this analysis, it was possible to conclude that TTF directly influences motivation (β = 0.632, p < .000), indicating that DSCTs users who perceive greater task-technology fit present higher motivation levels regarding the use of DSCTs.

Moreover, it is evident that TTF also has a direct effect on utilization (β = 0.283, p < .002), however, to a lower extent compared to motivation. This suggests that an increase in the TTF perceived by DSCT users will lead to an increase in the utilization of these means.

Additionally, motivation demonstrates a direct effect on utilization (β = 0.398, p < .000), indicating that DSCT users are more likely to use these tools if they possess a high level of motivation.

Lastly, TTF indirectly affects utilization through motivation (β = 0.251, p < .000), which implies that part of the influence of TTF on utilization is mediated by motivation, highlighting the importance of motivation as a mediator in the relationship between TTF and utilization.

Table 2 – Mediation Analysis

	Beta	**SD**	**t-Test**	**p-value**
TTF-> Motivation	.632	.049	12.895	<.000
TTF-> Utilization	.283	.091	3.112	<.002
Motivation-> Utilization	.398	.090	4.426	<.000
TTF -> Motivation->Utilization	.251	.058	4.347	<.000

After examining the mediators within the research model, we will delve into the moderator analysis. In statistical terms, moderation denotes a relationship in which changes between an independent and dependent variable are influenced by the value of the moderator variable (Memon et al., 2019). Figure 3 illustrates the impact of the statistically significant moderator, technology addiction, on the relationship between utilization and individual performance.

From the figure, it is evident that the technology addiction moderator induces a more substantial influence of utilization over individual performance among users with higher technology addiction.

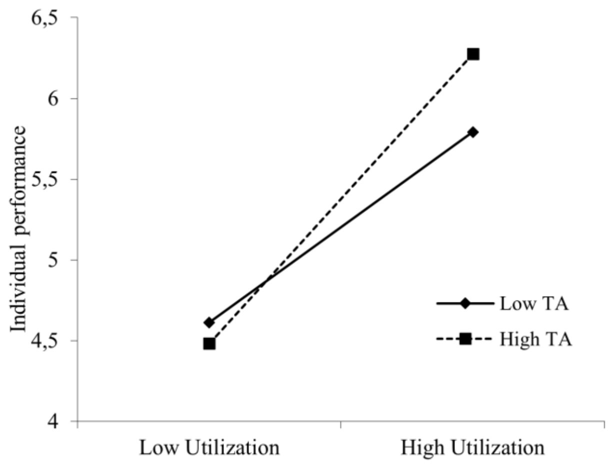

Figure 3 –Moderation effect of Technology Addiction on Individual Performance

Moreover, Figure 4 shows the effect of the moderator, severity of enforcement, on the relationship between utilization and individual performance. Hence, it is apparent that when DSCTs apply a lower level of severity of enforcement, it leads to a more significant influence of utilization over individual performance.

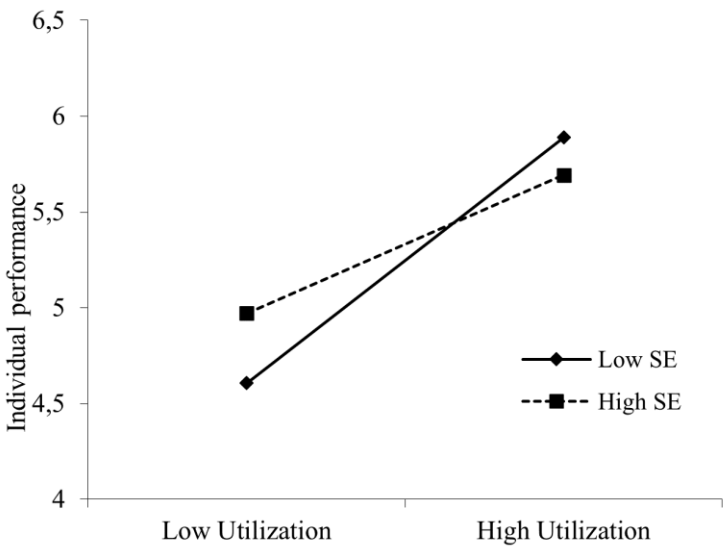

Figure 4 –Moderation effect of Severity of Enforcement on Individual Performance

6. DISCUSSION

The present research was driven by a core question: "What influences the individual performance of digital self-control tools?". To address it, a comprehensive theoretical framework was developed, integrating Goodhue & Thompson's (1995) task-technology fit (TTF) model with additional constructs, including self-control, technology addiction, motivation, continuance intention, and the severity of enforcement. The model's results generally corroborated our hypothesis, except for H1, H7a and H8.

This research provides valuable insights to developers currently designing DSCTs. It also offers a new perspective to the literature, as most studies regarding DSCTs focus on comprehending and analyzing the functionalities and effectiveness of these interventions. The following section delves into design implications and future research opportunities.

6.1. THEORETICAL IMPLICATIONS

Despite the plethora of DSCTs designed and introduced to the market in recent years, most studies on these interventions are not grounded in behavioral theory or construct. Consequently, our understanding of the effectiveness of these tools remains limited, requiring more clarity on the best approaches to designing and evaluating DSCTs (Monge Roffarello & De Russis, 2022). In this context, the present paper aimed to contribute to fill this gap by investigating the influence of DSCTs on individual performance, drawing upon Goodhue & Thompson's (1995) TTF model.

Interestingly, our study suggests that DSCT users tend to place greater value on technology characteristics rather than task characteristics, meaning that other technologies may already enable users to perform similar tasks. Hence, the allure for individuals lies in the technology itself (Kang, 2022).

Furthermore, our findings suggest that trait self-control plays a crucial role in shaping individuals' perceptions of the TTF provided by DSCTs. These results align with prior literature that verified the direct effect of various other individual characteristics on TTF. For instance, Gu and Wang (2009) demonstrated that openness and agreeableness significantly affected perceived TTF.

Lastly, our results highlighted the mediating role of motivation in the relationship between the utilization of DSCTs and the perceived TTF of the users. Hence, motivated users are more likely to perceive DSCTs as fitting their tasks, which, in turn, increases the utilization of these tools. These findings further corroborate prior literature that has shown the positive influence of motivation on TTF. This is exemplified in the study by Sun & Gao (2019), which found that motivation positively impacts users' TTF regarding mobile devices in language learning.

6.2. PRACTICAL IMPLICATIONS

Transitioning to the practical implications derived from our study's findings, we now present actionable insights to optimize DSCTs design with the aim of enhancing the utilization and individual performance derived from these interventions.

The current study's findings suggest that the characteristics of DSCTs directly influence the TTF perceived by its users. Recent research conducted by Monge Roffarello et al. (2023) has highlighted a critical limitation of traditional DSCTs: their tendency to overlook user context and intentions. This neglect usually results in unmet user expectations, ultimately leading to tool abandonment. Hence, it is imperative for developers, when designing DSCTs, to aim for a close alignment between the features of these tools and the tasks of users they are intended to support. By enhancing TTF through design, users are more likely to adhere to these tools and withdraw the benefits they present.

Our research also revealed that users' trait self-control affects the perceived TTF of DSCTs. This sheds light on another design opportunity for developers by tailoring these features to users' self-control levels. For instance, for users with low self-control, the tool might suggest more challenging goals or stricter settings to enhance TTF and, therefore, stimulate the utilization of these tools. Conversely, it might offer gentler reminders or more achievable objectives for highly self-controlled users.

Furthermore, our results indicate that motivation exerts a direct influence on DSCTs utilization, consistent with the findings of Biedermann et al. (2023), which noted that a lack of motivation can lead to discontinuation of the use of these tools. Monge Roffarello et al. (2023) further assert that DSCTs users' motivation tends to decline over time due to the sustained effort required. To address this limitation, developers should consider integrating motivational features within DSCTs, such as introducing gamification elements like badges, points, or rewards and incorporating social features, like sharing accomplishments with friends or joining communities within these tools. Another interesting approach proposed by Monge Roffarello et al. (2023) extends beyond technological solutions and comprises educational, social, and political dimensions in communicating DSCTs to the public. These strategies combined can be promising in enhancing user motivation and fostering consistent use of DSCTs.

Moreover, the present research provides evidence that technology addiction positively moderates the individual performance of DSCTs users, supporting earlier findings of Lyngs et al. (2022) that propose these tools are particularly beneficial for users who identify themselves as technology addicts.

Lastly, our results confirm that the severity of enforcement implemented by DSCTs moderates the individual performance of these means, corroborating previous findings in the literature indicating that DSCTs must provide a moderate level of enforcement to enhance adherence and user retention. According to Lukoff et al. (2022), minimal enforcement may enable users to bypass their objectives and fail to hold users responsible in moments of temptation. In contrast, excessive enforcement has been criticized by users for lacking flexibility in managing actual emergencies and evoking feelings of frustration, ultimately leading users to discontinue using these tools. Hence, when designing DSCTs, developers must ensure a balanced approach, offering a moderate level of enforcement to promote consistent usage and increase the individual performance of users.

7. CONCLUSIONS AND FUTURE RESEARCH

This paper has made a significant contribution to the emerging field of DSCTs by being the first to investigate their impact on individual performance. Previous research on DSCTs has often lacked a comprehensive theoretical foundation. By integrating Goodhue & Thompson's (1995) task-technology fit (TTF) model with constructs such as self-control, technology addiction, motivation, continuance intention, and severity of enforcement, we successfully addressed this gap in the literature.

The findings of this study provide compelling evidence that the technology characteristics of DSCTs and the self-control of users positively affected the perceived TTF of these individuals. Additionally, consistent with previous literature, we confirmed that TTF significantly influenced the utilization of DSCTs and that, consequently, utilization affects its users' individual performance. Our results also highlighted the mediating role of motivation in the relationship between DSCTs' utilization and users' perceived TTF. Notably, the moderators of technology addiction and severity of enforcement were found to have significant effects on individual performance beyond mere utilization.

Furthermore, our study provides crucial insights to developers and companies developing DSCTs to enhance the utilization and drive individual performance derived from these interventions.

We must acknowledge two main limitations in our study. Firstly, we employed a relatively small sample size, predominantly consisting of individuals under 25 years old. Hence, our results should be validated by a more extensive and diverse sample, encompassing individuals across diverse age groups. Second, it is crucial to mention potential biases in our survey results related to the constructs of technology addiction and self-control. These are sensitive topics that individuals may be reluctant to openly admit or discuss, which could influence the data collected. Future work must employ additional methods or measures to address these sensitivities and improve the results' reliability.

BIBLIOGRAPHICAL REFERENCES

Alamri, M. M., Almaiah, M. A., & Al-Rahmi, W. M. (2020, September 4). *The Role of Compatibility and Task-Technology Fit (TTF): On Social Networking Applications (SNAs) Usage as Sustainability in Higher Education*. Ieeexplore.ieee.org. https://ieeexplore.ieee.org/abstract/document/9186601

Almourad, M. B., Alrobai, A., Skinner, T., Hussain, M., & Ali, R. (2021). Digital wellbeing tools through users lens. *Technology in Society*, *67*, 101778. https://doi.org/10.1016/j.techsoc.2021.101778

Alturki, U., & Aldraiweesh, A. (2022). Adoption of Google Meet by Postgraduate Students: The Role of Task Technology Fit and the TAM Model. *Sustainability*, *14*(23), 15765. https://doi.org/10.3390/su142315765

Barlow, P., Reeves, A., McKee, M., Galea, G., & Stuckler, D. (2016). Unhealthy diets, obesity and time discounting: a systematic literature review and network analysis. *Obesity Reviews*, *17*(9), 810–819. https://doi.org/10.1111/obr.12431

Baumeister, R. F., Vohs, K. D., & Tice, D. M. (2007). The Strength Model of Self-Control. *Current Directions in Psychological Science*, *16*(6), 351–355. https://doi.org/10.1111/j.1467-8721.2007.00534.x

Bembenutty, H. (2021). Sustaining Motivation and Academic Delay of Gratification: Analysis and Applications. *Theory into Practice*. https://doi.org/10.1080/00405841.2021.1955555

Bickel, W. K., Johnson, M. W., Koffarnus, M. N., MacKillop, J., & Murphy, J. G. (2014). The Behavioral Economics of Substance Use Disorders: Reinforcement Pathologies and Their Repair. *Annual Review of Clinical Psychology*, *10*(1), 641–677. https://doi.org/10.1146/annurev-clinpsy-032813-153724

Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. *Psychopharmacology*, *146*(4), 447–454. https://doi.org/10.1007/pl00005490

Biedermann, D., Kister, S., Breitwieser, J., Weidlich, J., & Hendrik Drachsler. (2023). Use of digital self-control tools in higher education – a survey study. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12198-2

Błachnio, A., & Przepiorka, A. (2015). Dysfunction of Self-Regulation and Self-Control in Facebook Addiction. *Psychiatric Quarterly*, *87*(3), 493–500. https://doi.org/10.1007/s11126-015-9403-1

Brühlmann, F., Vollenwyder, B., Opwis, K., & Mekler, E. D. (2018). Measuring the “Why” of Interaction. *PsyArXiv (OSF Preprints)*. https://doi.org/10.1145/3173574.3173680

Burton-Jones, A., & Straub, D. W. (2006). Reconceptualizing System Usage: An Approach and Empirical Test. *Information Systems Research*, *17*(3), 228–246. https://www.jstor.org/stable/23015887?typeAccessWorkflow=login

Charlton, J. P. (2002). A factor-analytic investigation of computer “addiction” and engagement. *British Journal of Psychology*, *93*(3), 329–344. https://doi.org/10.1348/000712602760146242

Chen, C., Zhang, K. Z. K., Gong, X., Lee, M., & Wang, Y.-Y. (2021). Preventing relapse to information technology addiction through weakening reinforcement: A self-regulation perspective. *Information & Management*, *58*(5), 103485–103485. https://doi.org/10.1016/j.im.2021.103485

Cheung, T. T. L., Gillebaart, M., Kroese, F., & De Ridder, D. (2014). Why are people with high self-control happier? The effect of trait self-control on happiness as mediated by regulatory focus. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.00722

Chiesi, F., Bonacchi, A., Lau, C., Tosti, A. E., Marra, F., & Saklofske, D. H. (2020). Measuring self-control across gender, age, language, and clinical status: A validation study of the Italian version of the Brief Self- Control Scale (BSCS). *PLOS ONE*, *15*(8), e0237729. https://doi.org/10.1371/journal.pone.0237729

Cho, H., Choi, D., Kim, D., Kang, W. J., Choe, E. K., & Lee, S.-J. (2021). Reflect, not Regret: Understanding Regretful Smartphone Use with App Feature-Level Analysis. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–36. https://doi.org/10.1145/3479600

Christakou, A., Brammer, M., & Rubia, K. (2011). Maturation of limbic corticostriatal activation and connectivity associated with developmental changes in temporal discounting. *NeuroImage*, *54*(2), 1344–1354. https://doi.org/10.1016/j.neuroimage.2010.08.067

Cudo, A., Torój, M., Demczuk, M., & Francuz, P. (2019). Dysfunction of Self-Control in Facebook Addiction: Impulsivity Is the Key. *Psychiatric Quarterly*, *91*(1), 91–101. https://doi.org/10.1007/s11126-019-09683-8

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982–1003. https://www.jstor.org/stable/2632151

Ferrari, J. R., Stevens, E. B., & Jason, L. A. (2009). The Role of Self-Regulation in Abstinence Maintenance: Effects of Communal Living on Self-Regulation. *Journal of Groups in Addiction & Recovery*, *4*(1-2), 32–41. https://doi.org/10.1080/15560350802712371

Fibel, B., & Hale, W. D. (1978). The Generalized Expectancy for Success Scale: A new measure. *Journal of Consulting and Clinical Psychology, 46*(5), 924–931. https://doi.org/10.1037/0022-006X.46.5.924

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Franque, F. B., Oliveira, T., & Tam, C. (2022). Continuance Intention of Mobile Payment: TTF Model with Trust in an African Context. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-022-10263-8

Frost, R., & McNaughton, N. (2017). The neural basis of delay discounting: A review and preliminary model. *Neuroscience & Biobehavioral Reviews*, *79*, 48–65. https://doi.org/10.1016/j.neubiorev.2017.04.022

Fung, S., Kong, C. Y. W., & Huang, Q. (2020). Evaluating the Dimensionality and Psychometric Properties of the Brief Self-Control Scale Amongst Chinese University Students. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.02903

Gennari, R., Matera, M., Morra, D., Melonio, A., & Rizvi, M. (2023). Design for social digital well-being with young generations: Engage them and make them reflect. *International Journal of Human-Computer Studies*, *173*, 103006. https://doi.org/10.1016/j.ijhcs.2023.103006

Gökalp, Z. Ş., Saritepeci, M., & Durak, H. Y. (2022). The relationship between self-control and procrastination among adolescent: The mediating role of multi-screen addiction. *Current Psychology*. https://doi.org/10.1007/s12144-021-02472-2

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213. https://doi.org/10.2307/249689

Green, L., & Myerson, J. (2004). A Discounting Framework for Choice with Delayed and Probabilistic Rewards. *Psychological Bulletin*, *130*(5), 769–792. https://doi.org/10.1037/0033-2909.130.5.769

Griffiths, M. D. (2018). Classifying behavioural addictions: the DSM, and over-pathologising everyday life. *Psychology Review*, *23*(3), 18–21. https://irep.ntu.ac.uk/id/eprint/32582/

Gschwandtner, A., Jewell, S., & Kambhampati, U. S. (2021). Lifestyle and Life Satisfaction: The Role of Delayed Gratification. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-021-00440-y

Gu, L., & Wang, J. (2009). A study of exploring the “big five” and task technology fit in webbased decision support systems. *Issues in Information Systems*, *10*.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). An Introduction to Structural Equation Modeling. *Classroom Companion: Business*, 1–29. https://doi.org/10.1007/978-3-030-80519-7_1

Hair, J., Tomas, G., Hult, M., Ringle, C., Sarstedt, M., Danks, N., & Ray, S. (2021). *Classroom Companion: Business Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R A Workbook*. https://library.oapen.org/bitstream/handle/20.500.12657/51463/9783030805197.pdf?sequence=1#page=88

Hekler, E. B., Klasnja, P., Froehlich, J. E., & Buman, M. P. (2013). Mind the theoretical gap. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/2470654.2466452

Hoerger, M., Quirk, S. W., & Weed, N. C. (2011). Development and validation of the Delaying Gratification Inventory. *Psychological Assessment*, *23*(3), 725–738. https://doi.org/10.1037/a0023286

Howard, M. C., & Rose, J. C. (2018). Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. *Information & Management*. https://doi.org/10.1016/j.im.2018.12.002

Huffman, D., Maurer, R., & Mitchell, O. S. (2019). Time discounting and economic decision-making in the older population. *The Journal of the Economics of Ageing*, *14*, 100121. https://doi.org/10.1016/j.jeoa.2017.05.001

Jamir, L., Duggal, M., Nehra, R., Singh, P., & Grover, S. (2019). Epidemiology of technology addiction among school students in rural India. *Asian Journal of Psychiatry*, *40*, 30–38. https://doi.org/10.1016/j.ajp.2019.01.009

Kang, H.-J., Han, J., & Kwon, G. H. (2022). The Acceptance Behavior of Smart Home Health Care Services in South Korea: An Integrated Model of UTAUT and TTF. *International Journal of*

Environmental Research and Public Health, *19*(20), 13279. https://doi.org/10.3390/ijerph192013279

Kaplan, B. A., Amlung, M., Reed, D. D., Jarmolowicz, D. P., McKerchar, T. L., & Lemley, S. M. (2016). Automating Scoring of Delay Discounting for the 21- and 27-Item Monetary Choice Questionnaires. *The Behavior Analyst*, *39*(2), 293–304. https://doi.org/10.1007/s40614-016-0070-9

Kirby, K. N., & MarakoviĆ, N. N. (1996). Delay-discounting probabilistic rewards: Rates decrease as amounts increase. *Psychonomic Bulletin & Review*, *3*(1), 100–104. https://doi.org/10.3758/bf03210748

Kirby, K. N., Petry, N. M., & Bickel, W. K. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental Psychology. General*, *128*(1), 78–87. https://doi.org/10.1037//0096-3445.128.1.78

Kloker, S. (2020). Non-addictive Information Systems. *Information Systems Frontiers*, *22*(3), 549–562. https://doi.org/10.1007/s10796-020-10011-w

Kotabe, H. P., & Hofmann, W. (2015). On Integrating the Components of Self-Control. *Perspectives on Psychological Science*, *10*(5), 618–638. https://doi.org/10.1177/1745691615593382

Kovács, G., Wu, Z., & Bernstein, M. S. (2021). Not Now, Ask Later: Users Weaken Their Behavior Change Regimen Over Time, But Expect To Re-Strengthen It Imminently. *ArXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2101.11743

Kwak, M.-J., Cho, H., & Kim, D.-J. (2022). The Role of Motivation Systems, Anxiety, and Low Self-Control in Smartphone Addiction among Smartphone-Based Social Networking Service (SNS) Users. *International Journal of Environmental Research and Public Health*, *19*(11), 6918. https://doi.org/10.3390/ijerph19116918

Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. *Computers in Human Behavior*, *25*(3), 778–784. https://doi.org/10.1016/j.chb.2009.02.006

Li, H., Guo, Y., & Yu, Q. (2019). Self-control makes the difference: The psychological mechanism of dual processing model on internet addicts' unusual behavior in intertemporal choice. *Computers in Human Behavior*, *101*, 95–103. https://doi.org/10.1016/j.chb.2019.07.010

Li, Q., Tian, M., Taxer, J., Zheng, Y., Wu, H., Sun, S., & Liu, X. (2016). Problematic Internet Users' Discounting Behaviors Reflect an Inability to Delay Gratification, Not Risk Taking. *Cyberpsychology, Behavior, and Social Networking*, *19*(3), 172–178. https://doi.org/10.1089/cyber.2015.0295

Li, Q., Xiang, G., Song, S., Huang, X., & Chen, H. (2021). Examining the Associations of Trait Self-control with Hedonic and Eudaimonic Well-being. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-021-00418-w

Li, S., Ren, P., Chiu, M. M., Wang, C., & Lei, H. (2021). The Relationship Between Self-Control and Internet Addiction Among Students: A Meta-Analysis. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.735755

Lin, H.-C., Han, X., Lyu, T., Ho, W.-H., Xu, Y., Hsieh, T.-C., Zhu, L., & Zhang, L. (2020). *Task-technology fit analysis of social media use for marketing in the tourism and hospitality industry: a systematic literature review*. https://www.emerald.com/insight/content/doi/10.1108/IJCHM-12-2019-1031/full/html?casa_token=RemKLK112x8AAAAA:eIcAmrZaIKvCicgDrztmq8KF8Tgh0mscdCR6K5TspRTvEUDIakpsxfzy2fsFXrS70lXGfgmmhs3Ff9Osj2yvSKPexNepRmCek3-9AT2eGqfbi6a2ghmK

Lindner, C., Nagy, G., & Retelsdorf, J. (2015). The dimensionality of the Brief Self-Control Scale—An evaluation of unidimensional and multidimensional applications. *Personality and Individual Differences*, *86*, 465–473. https://doi.org/10.1016/j.paid.2015.07.006

Lukoff, K., Lyngs, U., & Alberts, L. (2022). *Designing to Support Autonomy and Reduce Psychological Reactance in Digital Self-Control Tools*. https://kailukoff.com/wp-content/uploads/2022/03/lukoff_sdt_workshop_chi22.pdf

Lukoff, K., Lyngs, U., Shirokova, K., Rao, R., Tian, L., Zade, H., Munson, S. A., & Hiniker, A. (2023). *SwitchTube: A Proof-of-Concept System Introducing "Adaptable Commitment Interfaces" as a Tool for Digital Wellbeing*. https://doi.org/10.1145/3544548.3580703

Lukoff, K., Yu, C., Kientz, J., & Hiniker, A. (2018). What Makes Smartphone Use Meaningful or Meaningless? *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *2*(1), 1–26. https://doi.org/10.1145/3191754

Lyngs, U. (2019). *Defining digital wellbeing*. https://ulriklyngs.com/pdfs/2019-02-08_Lyngs_workshop_digi_wellbeing.pdf

Lyngs, U. (2019). *Ulysses in cyberspace: examining the effectiveness of design patterns for digital self-control* (Doctoral dissertation, University of Oxford).

Lyngs, U., & Lukoff, K. (2022). *Designing for Meaningful Interactions and Digital Wellbeing*. https://kailukoff.com/wp-content/uploads/2022/06/2022-lyngs-lukoff-dw_workshop_avi.pdf

Lyngs, U., Lukoff, K., Csuka, L., Slovák, P., Van Kleek, M., & Shadbolt, N. (2022). The Goldilocks level of support: Using user reviews, ratings, and installation numbers to investigate digital self-control tools. *International Journal of Human-Computer Studies*, *166*, 102869. https://doi.org/10.1016/j.ijhcs.2022.102869

Lyngs, U., Lukoff, K., Slovak, P., Binns, R., Slack, A., Inzlicht, M., Van Kleek, M., & Shadbolt, N. (2019). Self-Control in Cyberspace. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300361

Madlock, P. E., & Hessling, C. N. (2020). The Technological Smoke Break: An Assessment of Technology Addiction in the Workplace. *International Journal of Business Communication*, 232948842091406. https://doi.org/10.1177/2329488420914069

Manapat, P. D., Edwards, M. C., MacKinnon, D. P., Poldrack, R. A., & Marsch, L. A. (2019). A Psychometric Analysis of the Brief Self-Control Scale. *Assessment*, *28*(2), 107319111989002. https://doi.org/10.1177/1073191119890021

Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., Cham, T., Tunku, U., Rahman, A., & Kajang, M. (2019). Journal of Applied Structural Equation Modeling MODERATION ANALYSIS: ISSUES AND GUIDELINES. *Journal of Applied Structural Equation Modeling*, *3*(1), 2590–4221. https://jasemjournal.com/wp-content/uploads/2019/10/2019-Memon-et-al-Moderation.pdf

Mischel, W. (1996). *From good intentions to willpower*. Psycnet.apa.org. https://psycnet.apa.org/record/1996-98326-009

Monge Roffarello, A., & De Russis, L. (2019). The Race Towards Digital Wellbeing. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems - CHI '19*. https://doi.org/10.1145/3290605.3300616

Monge Roffarello, A., & De Russis, L. (2021). Coping with Digital Wellbeing in a Multi-Device World. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445076

Monge Roffarello, A., & De Russis, L. (2022). Achieving Digital Wellbeing Through Digital Self-Control Tools: A Systematic Review and Meta-Analysis. *ACM Transactions on Computer-Human Interaction*. https://doi.org/10.1145/3571810

Monge Roffarello, A., & De Russis, L. (2023a). *Nudging Users or Redesigning Interfaces? Evaluating Novel Strategies for Digital Wellbeing Through inControl*. https://doi.org/10.1145/3582515.3609523

Monge Roffarello, A., & De Russis, L. (2023b). *Nudging Users Towards Conscious Social Media Use*. https://doi.org/10.1145/3565066.3608703

Monge Roffarello, A., & De Russis, L. (2023c). Teaching and learning "Digital Wellbeing." *Future Generation Computer Systems*, *149*, 494–508. https://doi.org/10.1016/j.future.2023.08.003

Monge Roffarello, A., De Russis, L., Lottridge, D., & Cecchinato, M. E. (2023). Understanding digital wellbeing within complex technological contexts. *International Journal of Human-Computer Studies*, *175*, 103034. https://doi.org/10.1016/j.ijhcs.2023.103034

Morean, M. E., DeMartini, K. S., Leeman, R. F., Pearlson, G. D., Anticevic, A., Krishnan-Sarin, S., Krystal, J. H., & O'Malley, S. S. (2014). Psychometrically improved, abbreviated versions of three classic measures of impulsivity and self-control. *Psychological Assessment*, *26*(3), 1003–1020. https://doi.org/10.1037/pas0000003

Mueller, I. M., Spinath, F. M., Friese, M., & Hahn, E. (2022). Genetics, Parenting, and Family Functioning – What Drives the Development of Self-Control from Adolescence to Adulthood? *Journal of Personality*. https://doi.org/10.1111/jopy.12723

Nilsen, F. A., Bang, H., Boe, O., Martinsen, Ø. L., Lang-Ree, O. C., & Røysamb, E. (2020). The Multidimensional Self-Control Scale (MSCS): Development and validation. *Psychological Assessment*, *32*(11). https://doi.org/10.1037/pas0000950

Odum, A. L. (2011). Delay Discounting: I'm a K, You're a K. *Journal of the Experimental Analysis of Behavior*, *96*(3), 427–439. https://doi.org/10.1901/jeab.2011.96-423

Odum, A. L., Becker, R. J., Haynes, J. M., Galizio, A., Frye, C. C. J., Downey, H., Friedel, J. E., & Perez, D. M. (2020). Delay discounting of different outcomes: Review and theory. *Journal of the Experimental Analysis of Behavior*, *113*(3), 657–679. https://doi.org/10.1002/jeab.589

Pereira, R., & Tam, C. (2021). Impact of enjoyment on the usage continuance intention of video-on-demand services. *Information & Management*, *58*(7), 103501. https://doi.org/10.1016/j.im.2021.103501

Peters, D., Calvo, R. A., & Ryan, R. M. (2018). Designing for Motivation, Engagement and Wellbeing in Digital Experience. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00797

Petrosyan, A. (2023a, July 27). *Time spent online worldwide 2023*. Statista. https://www.statista.com/statistics/1380282/daily-time-spent-online-global/#:~:text=Daily%20time%20spent%20online%20by%20users%20worldwide%202023&text=As%20of%20the%20first%20quarter

Petrosyan, A. (2023b, September 22). *Internet and Social Media Users in the World 2023*. Statista. https://www.statista.com/statistics/617136/digital-population-worldwide/#:~:text=Worldwide%20digital%20population%202023&text=As%20of%20July%202023%2C%20there

Pritschmann, R. K., Yurasek, A. M., & Yi, R. (2021). A review of cross-commodity delay discounting research with relevance to addiction. *Behavioural Processes*, *186*, 104339. https://doi.org/10.1016/j.beproc.2021.104339

Purwanto, A. (2021, December 11). *Partial Least Squares Structural Squation Modeling (PLS-SEM) Analysis for Social and Management Research: A Literature Review*. Social Science Research Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3982764

Qi, H., Bi, C., Kang, Q., Wu, Q., & Wu, D. (2022). Far from the Future: Internet Addiction Association with Delay Discounting Among Adolescence. *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-022-00951-6

Ren, Y., Tang, R., & Li, M. (2022). The relationship between delay of gratification and work engagement: The mediating role of job satisfaction. *Heliyon*, *8*(8), e10111. https://doi.org/10.1016/j.heliyon.2022.e10111

Sarstedt, M., Hair, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2020). Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses! *International Journal of Market Research*, *62*(3), 288–299. https://doi.org/10.1177/1470785320915686

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial Least Squares Structural Equation Modeling. *Handbook of Market Research*, 1–47. https://doi.org/10.1007/978-3-319-05542-8_15-2

Saville, B. K., Gisbert, A., Kopp, J., & Telesco, C. (2010). Internet addiction and delay discounting in college students. *The psychological record*, *60*, 273-286.

Schulz van Endert, T. (2021). Addictive use of digital devices in young children: Associations with delay discounting, self-control, and academic performance. *PLOS ONE*, *16*(6), e0253058. https://doi.org/10.1371/journal.pone.0253058

Schulz van Endert, T., & Mohr, P. N. C. (2020). Likes and impulsivity: Investigating the relationship between actual smartphone use and delay discounting. *PLOS ONE*, *15*(11), e0241383. https://doi.org/10.1371/journal.pone.0241383

Schwartz, R. (2019). *Ulysses' ropes and the inherent limits of digital self-control tools*. https://libraopen.lib.virginia.edu/downloads/0g354f345

Schwartz, R. X., Monge Roffarello, A., De Russis, L., & Apostolellis, P. (2021). Reducing Risk in Digital Self-Control Tools: Design Patterns and Prototype. *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411763.3451843

Serenko, A., & Turel, O. (2015). Integrating Technology Addiction and Use: An Empirical Investigation of Facebook Users. *AIS Transactions on Replication Research*, *1*, 1–18. https://doi.org/10.17705/1atrr.00002

Serenko, A., & Turel, O. (2020). Directing Technology Addiction Research in Information Systems. *ACM SIGMIS Database: The Database for Advances in Information Systems*, *51*(3), 81–96. https://doi.org/10.1145/3410977.3410982

Serenko, A., & Turel, O. (2022). Directing Technology Addiction Research in Information Systems. *ACM SIGMIS Database: The Database for Advances in Information Systems*, *53*(3), 71–90. https://doi.org/10.1145/3551783.3551789

Sherer, J., & Levounis, P. (2022). Technological Addictions. *Current Psychiatry Reports*, *24*(9), 399–406. https://doi.org/10.1007/s11920-022-01351-2

Small, G. (2020). Brain health consequences of digital technology use. *Dialogues in Clinical Neuroscience*, *22*(2), 179–187. https://doi.org/10.31887/dcns.2020.22.2/gsmall

Spies, R., Grobbelaar, S., & Botha, A. (2020). A Scoping Review of the Application of the Task-Technology Fit Theory. *Lecture Notes in Computer Science*, 397–408. https://doi.org/10.1007/978-3-030-44999-5_33

Sun, Y., & Gao, F. (2019). An investigation of the influence of intrinsic motivation on students' intention to use mobile devices in language learning. *Educational Technology Research and Development*, *68*(3), 1181–1198. https://doi.org/10.1007/s11423-019-09733-9

Tam, C., & Oliveira, T. (2016). Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective. *Computers in Human Behavior*, *61*, 233–244. https://doi.org/10.1016/j.chb.2016.03.016

Tam, C., & Oliveira, T. (2019). Does culture influence m-banking use and individual performance? *Information & Management*, *56*(3), 356–363. https://doi.org/10.1016/j.im.2018.07.009

Tam, C., Loureiro, A., & Oliveira, T. (2020). The individual performance outcome behind e-commerce: Integrating information systems success and overall trust. *Internet Research*, *30*(2), 439-462.

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High Self-Control Predicts Good Adjustment, Less Pathology, Better Grades, and Interpersonal Success. *Journal of Personality*, *72*(2), 271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x

Taylor, I. M., Boat, R., & Murphy, S. L. (2018). Integrating theories of self-control and motivation to advance endurance performance. *International Review of Sport and Exercise Psychology*, 1–20. https://doi.org/10.1080/1750984x.2018.1480050

Thomas, N. M., Choudhari, S. G., Gaidhane, A. M., & Syed, Z. Q. (2022). "Digital Wellbeing": The Need of the Hour in Today's Digitalized and Technology Driven World!. *Cureus*, *14*(8). https://doi.org/10.7759/cureus.27743

Turel, O., He, Q., Brevers, D., & Bechara, A. (2018). Delay discounting mediates the association between posterior insular cortex volume and social media addiction symptoms. *Cognitive, Affective, & Behavioral Neuroscience*, *18*(4), 694–704. https://doi.org/10.3758/s13415-018-0597-1

Turel, O., Qahri-Saremi, H., & Vaghefi, I. (2021). Introduction to Special Issue: Dark Sides of Digitalization. *International Journal of Electronic Commerce*, 1–9. https://doi.org/10.1080/10864415.2021.1887694

Vanden Abeele, M. M. P. (2020). Digital Wellbeing as a Dynamic Construct. *Communication Theory*, *31*(4). https://doi.org/10.1093/ct/qtaa024

Vanduhe, V. Z., Nat, M., & F.Hasan, H. (2020). Continuance intentions to use gamification for training in higher education: Integrating the technology acceptance model (TAM), social motivation and task technology fit (TTF). *IEEE Access*, 1–1. https://doi.org/10.1109/access.2020.2966179

Wang, X., Liang, W., Liu, J., Zhang, C.-Q., Duan, Y., Si, G., Bu, D., & Zhao, D. (2022). Further Examination of the Psychometric Properties of the Multicomponent Mental Health Literacy Scale: Evidence from Chinese Elite Athletes. *International Journal of Environmental Research and Public Health*, *19*(19), 12620. https://doi.org/10.3390/ijerph191912620

Watson, S. J., & Milfont, T. L. (2017). A short-term longitudinal examination of the associations between self-control, delay of gratification and temporal considerations. *Personality and Individual Differences*, *106*, 57–60. https://doi.org/10.1016/j.paid.2016.10.023

Xiang, M.-Q., Lin, L., Wang, Z.-R., Li, J., Xu, Z., & Hu, M. (2020). Sedentary Behavior and Problematic Smartphone Use in Chinese Adolescents: The Moderating Role of Self-Control. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.03032

Zaidi, S., Kazi, A. M., Riaz, A., Ali, A., Najmi, R., Jabeen, R., Khudadad, U., & Sayani, S. (2020). Operability, Usefulness, and Task-Technology Fit of an mHealth App for Delivering Primary Health Care Services by Community Health Workers in Underserved Areas of Pakistan and Afghanistan: Qualitative Study. *Journal of Medical Internet Research*, *22*(9), e18414. https://doi.org/10.2196/18414

APPENDIX

Appendix A – Survey Items

Construct	Item	Description	Adapted from
Task Characteristics	TASK1	I need to focus on important yet demanding tasks overindulging in guilty pleasures.	(Lyngs, 2019)
	TASK2	I need to improve my time management skills.	
	TASK3	I need to enhance my digital wellbeing by reducing device overuse.	
Technology Characteristics	TECH1	Digital self-control tools provide features that block or suppress distractions.	(Lyngs, 2019)
	TECH2	Digital self-control tools provide features for tracking and visualising application and device use.	
	TECH3	Digital self-control tools provide features that prompt user's usage goals.	
	TECH4	Digital self-control tools provide rewards for using devices in specific ways.	
Task-Technology Fit	TTF1	Digital self-control tools blocking features are appropriate.	(Franque et al., 2022)
	TTF2	Digital self-control tools tracking features are appropriate.	
	TTF3	Digital self-control tools goal advancement features are appropriate.	
	TTF4	Digital self-control tools reward features are appropriate.	
	TTF5	In general, digital self-control tools features are enough.	
Utilization	U1	I use digital self-control tools to focus on important yet demanding tasks over indulging in guilty pleasures.	(Lyngs, 2019)
	U2	I use digital self-control tools to improve my time management skills.	
	U3	I use digital self-control tools to enhance my digital wellbeing by reducing device overuse.	
Individual Performance	IP1	Digital self-control tools enable me to accomplish tasks more quickly.	(Tam & Oliveira, 2020)
	IP2	Digital self-control tools make it easier for me to accomplish tasks.	
	IP3	Digital self-control tools increase my productivity.	
Self-Control	SC1	I can stop myself from being on digital devices when I know it is wrong.	(Chen et al., 2021)

	SC2	I am not self-indulgent in being on digital devices.	
	SC3	I am not on digital devices on the spur of the moment.	
Technology Addiction	TA1	I sometimes neglect important things because of my interest in digital devices.	(Serenko & Turel, 2015)
	TA2	When I am not using digital devices, I often feel agitated.	
	TA3	I have made unsuccessful attempts to reduce the time I spent on digital devices.	
	TA4	I think that I am addicted to digital devices.	
Motivation	M1	The benefits of using digital self-control tools are important to me.	(Brühlmann et al., 2018)
	M2	Using digital self-control tools is a good way to achieve what I need right now.	
	M3	Using digital self-control tools is a wise and practical thing to do.	
Severity of Enforcement	SE1	Digital self-control tools feel intrusive.	(Peters et al., 2018)
	SE2	Digital self-control tools feel controlling.	
	SE3	I feel pressured by digital self-control tools.	
Continuance Intention	CI1	I intend to continue using digital self-control tools rather than discontinue its use.	(Pereira & Tam, 2021)
	CI2	My intentions are to continue using digital self-control tools rather than use any alternative means.	
	CI3	I will use digital self-control tools on a regular basis in the future.	

Appendix B – PLS Loading and Cross-loadings

Constructs		TAC	TEC	TTF	UT	IP	SC	TA	MT	SE	CI
Task Characteristics	TASK 1	**0.596**	0.264	0.166	0.399	0.272	-0.022	0.225	0.253	-0.057	0.278
	TASK 2	**0.667**	0.167	0.140	0.320	0.182	0.046	0.175	0.192	0.068	0.266
	TASK 3	**0.905**	0.390	0.368	0.512	0.231	-0.007	0.227	0.375	-0.093	0.298
Technology Characteristics	TECH 1	0.431	**0.695**	0.460	0.545	0.388	0.115	0.075	0.381	-0.167	0.353
	TECH 2	0.403	**0.813**	0.573	0.426	0.267	0.155	-0.013	0.354	-0.039	0.233
	TECH 3	0.302	**0.847**	0.618	0.325	0.312	0.108	0.086	0.387	-0.024	0.245
	TECH 4	0.116	**0.752**	0.485	0.267	0.250	0.090	-0.046	0.260	-0.032	0.100
Task-Technology Fit	TTF1	0.364	0.569	**0.804**	0.533	0.419	0.163	0.101	0.587	-0.219	0.501
	TTF2	0.226	0.469	**0.760**	0.389	0.334	0.100	0.100	0.510	-0.318	0.385
	TTF3	0.311	0.591	**0.857**	0.473	0.455	0.261	0.057	0.556	-0.141	0.521
	TTF4	0.214	0.591	**0.785**	0.416	0.323	0.216	0.162	0.426	-0.018	0.311
	TTF5	0.212	0.458	**0.679**	0.333	0.236	0.160	-0.140	0.344	-0.057	0.270
Utilization	U1	0.465	0.364	0.434	**0.829**	0.570	0.154	0.212	0.520	-0.017	0.500
	U2	0.482	0.377	0.441	**0.860**	0.584	0.214	0.092	0.484	0.083	0.387
	U3	0.467	0.491	0.516	**0.785**	0.412	0.123	0.188	0.486	-0.045	0.398
Individual Performance	IP1	0.264	0.384	0.340	0.543	**0.903**	0.190	0.024	0.454	-0.017	0.403
	IP2	0.257	0.289	0.448	0.578	**0.925**	0.248	0.029	0.554	-0.045	0.532
	IP3	0.295	0.392	0.478	0.629	**0.930**	0.207	0.018	0.547	-0.096	0.539
Self-control	SC1	-0.146	0.114	0.065	0.077	0.070	**0.560**	-0.208	0.032	0.138	-0.013
	SC2	0.010	0.141	0.208	0.188	0.219	**0.896**	-0.211	0.189	0.064	0.271
	SC3	0.034	0.118	0.226	0.178	0.216	**0.880**	-0.029	0.137	0.094	0.093

Technology Addiction	TA1	0.225	0.076	0.064	0.165	0.055	-0.155	**0.810**	0.173	0.133	-0.066
	TA2	0.237	-0.002	0.059	0.106	0.032	-0.095	**0.731**	0.239	0.259	0.115
	TA3	0.231	-0.009	0.087	0.219	0.022	-0.117	**0.891**	0.175	0.158	0.051
	TA4	0.236	0.063	0.049	0.115	-0.045	-0.131	**0.858**	0.174	0.318	0.001
Motivation	M1	0.377	0.295	0.477	0.566	0.521	0.119	0.271	**0.887**	0.023	0.622
	M2	0.343	0.388	0.544	0.545	0.540	0.184	0.193	**0.918**	-0.075	0.593
	M3	0.344	0.498	0.667	0.514	0.469	0.156	0.144	**0.888**	-0.190	0.636
Severity	SE1	-0.142	-0.102	-0.167	-0.074	-0.039	0.203	0.142	-0.169	**0.864**	-0.120
of Enforcement	SE2	-0.031	-0.049	-0.184	0.024	-0.058	0.108	0.164	-0.091	**0.932**	-0.150
	SE3	-0.032	-0.069	-0.178	0.050	-0.060	0.007	0.310	-0.027	**0.901**	-0.170
Continuance Intention	CI1	0.365	0.277	0.452	0.463	0.484	0.141	0.051	0.638	-0.150	**0.885**
	CI2	0.293	0.230	0.483	0.425	0.429	0.236	-0.046	0.539	-0.189	**0.870**
	CI3	0.332	0.289	0.479	0.510	0.535	0.126	0.051	0.670	-0.118	**0.942**

Appendix C - Reliability and validity measures (CR, CA, and AVE) of latent variables

	Mean	SD	CA	CR	CI	IP	MT	SC	SE	TAC	TTF	TA	TEC	UT
CI	5.186	0.920	0.882	0.894	**0.900**									
IP	5.274	0.983	0.909	0.917	0.539	**0.919**								
MT	5.299	0.801	0.880	0.883	0.688	0.567	**0.898**							
SC	4.280	1.046	0.725	0.830	0.181	0.235	0.171	**0.794**						
SE	3.751	1.216	0.884	0.917	-0.166	-0.060	-0.095	0.103	**0.899**					
TAC	5.689	0.831	0.609	0.814	0.368	0.296	0.394	0.000	-0.065	**0.735**				
TTF	5.359	0.865	0.837	0.851	0.522	0.464	0.632	0.234	-0.197	0.348	**0.779**			
TA	4.570	1.203	0.847	0.916	0.025	0.025	0.223	-0.151	0.237	0.277	0.083	**0.824**		
TEC	5.408	0.862	0.783	0.798	0.296	0.385	0.444	0.151	-0.077	0.401	0.691	0.035	**0.779**	
UT	5.497	0.981	0.765	0.770	0.520	0.637	0.602	0.200	0.011	0.570	0.558	0.198	0.493	**0.825**

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa