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Problematic Digital Technology Use Scale Among University Students: A Validity and Reliability Study

Üniversite Öğrencilerinde Sorunlu Dijital Teknoloji Kullanma Ölçeği: Geçerlilik ve Güvenirlik Çalışması

Hasan Tutar[1], Hakan Tahiri Mutlu[2]

[1] Bolu Abant Izzet Baysal University, Faculty of Communication, Department of Public Relations, Bolu / Türkiye
[2] Bolu Abant Izzet Baysal University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Bolu / Türkiye

Özet

Dijital teknolojilerin kullanım yaygınlığı arttıkça, dijital teknoloji kullanımına bağlı sorunların da yaygınlığı giderek artmaktadır. Bu çalışmada, sorunlu dijital teknoloji kullanımı olduğu varsayılan üniversite öğrencilerinin bu konudaki algılarını ölçmeye yarayan bir ölçeğin geliştirilmesi amaçlanmıştır. Ölçek geliştirme sürecinde, sorunlu dijital teknoloji kullanımına ilişkin ortak temaları, faktörleri, nedenleri ve sonuçları belirlemek için öncelikle literatür taraması yapılmış; daha sonra ölçeğin nitel kısmında üniversite öğrencileriyle görüşülerek sorunlu dijital teknoloji kullanımına dair görüşlerini yansıtan bir ölçek madde havuzu oluşturulmuştur. Sonraki aşamada, pilot çalışma yapılarak maddelerin sadeleştirilmesi amacıyla keşfedici ve doğrulayıcı yapı analizi gerçekleştirilmiştir. Dijital teknoloji kullanımının boyutlarını belirlemek için yapılan keşfedici faktör analizi sonucunda, birbiriyle örtüşen maddelerin çıkarılmasıyla ölçek iyileştirilmiştir. Faktör analizi sonucunda ölçeğin "Dürtü Kontrolü Kaybı", "Sosyal İzolasyon" ve "Fiziksel ve Zihinsel Yorgunluk" olmak üzere üç faktörden oluştuğu tespit edilmiştir. Belirlenen faktör yapısının istikrarını değerlendirmek için doğrulayıcı faktör analizi (DFA) ve ölçeğin iç tutarlılığını değerlendirmek için Cronbach's alpha güvenilirlik analizi yapılmıştır. Analizler, ölçeğin Cronbach alfa katsayısının yüksek iç tutarlılığa sahip olduğunu (0,918) göstermiştir. Sonuç olarak, geliştirilen ölçeğin araştırmacılar ve uygulayıcılar için sorunlu dijital teknoloji kullanımını değerlendirmede güvenilir ve geçerli bir araç olduğu sonucuna varılmıştır.

Anahtar Kelimeler: Dijital Teknoloji, Dijital Bağımlılık, Sorunlu Dijital Teknoloji Kullanımı Ölçeği

Abstract

As the prevalence of digital technology increases, issues related to its use have also become more widespread. This study aimed to develop a scale to measure the perceptions of university students, assumed to experience problematic digital technology use, regarding their usage patterns. During the scale development process, a literature review was conducted to identify common themes, factors, causes, and consequences of problematic digital technology use. Subsequently, in the qualitative phase, interviews were conducted with university students to gather their views, which were used to create an initial pool of scale items reflecting problematic digital technology use. In the next stage, a pilot study was conducted, and exploratory and confirmatory factor analyses were performed to refine and simplify the scale items. Exploratory factor analysis (EFA) was used to identify the dimensions of digital technology use, and overlapping items were removed to improve the scale. The factor analysis revealed that the scale consisted of three factors: Loss of Impulse Control, Social Isolation, and Physical and Mental Fatigue. Confirmatory factor analysis (CFA) was conducted to assess the stability of the factor structure, and Cronbach's alpha reliability analysis was performed to evaluate the internal consistency of the scale. The analysis indicated that the Cronbach's alpha coefficient demonstrated a high level of internal consistency (0.918). In conclusion, the scale developed was found to be a reliable and valid tool for researchers and practitioners aiming to assess problematic digital technology use.

Keywords: Digital Technology, Digital Addiction, Problematic Digital Technology use Scale

Scale development studies are often necessitated by factors such as the emergence of new concepts, events, phenomena, or conditions; the absence of scales measuring the structure and variables to be investigated; differences in the target audience; and inadequacies in psychometric properties (Erkuş, 2021; Yurdabakan & Çüm, 2017). In a landscape where digital technology permeates every aspect of life, it is imperative to identify, elucidate, and raise awareness about problematic areas arising from these technologies. While technological advancements bring about significant changes in individual and public life, they also present numerous challenges.

İletişim / Correspondence:
Assoc. Prof. Hakan Tahiri Mutlu
Bolu Abant Izzet Baysal University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Bolu
e-posta: tahirimutlu@ibu.edu.tr

Yükseköğretim Dergisi / TÜBA Higher Education Research/Review (TÜBA-HER), 14(3), 135-146.
Geliş tarihi / Received: Mart / March 18, 2024; **Kabul tarihi / Accepted:** Nisan / April 17, 2024
Bu makalenin atıf künyesi / How to cite this article: Tutar, H. & Mutlu, H. T. (2024). Problematic Digital Technology Use Scale Among University Students: A Validity and Reliability Study. *Yükseköğretim Dergisi, 14*(3), 135-146. https://doi.org/10.53478/yuksekogretim.1454547

ORCID: H. Tutar: 0000-0001-8383-1464; H. T. Mutlu: 0000-0002-8964-2696

One such challenge is problematic digital technology usage, particularly among young people (Smith & Doe, 2018; Johnson & Brown, 2019; Singha et al., 2023; Sharma, 2023). "Nomophobia," the fear of being without a smartphone, has become so ingrained in daily life that it warrants examination as a phobia due to its ability to induce anxiety. Problematic digital technology usage includes excessive use of digital devices and platforms, which can lead to digital addiction, loss of impulse control, social isolation, and physical and mental fatigue. Manifestations of problematic digital technology usage range from compulsively checking notifications or losing track of time while browsing social media feeds to experiencing anxiety when separated from digital devices, often negatively impacting daily routines (Lee & Lee, 2017; Rosen & Carrier, 2015; Kuss & Griffiths, 2017). Concerns regarding excessive screen time and digital addiction are known to cause various psychosomatic issues, from compromised mental well-being to strained interpersonal relationships, diminishing overall quality of life.

Problematic digital technology usage stems from complex causes, and its impact on human life varies. However, raising awareness of this issue is crucial for maintaining healthy individuals and communities (Cho & Park, 2018; Panova & Carbonell, 2018; Kim et al., 2017; Wegmann et al., 2019). The widespread adoption of digital technology in contemporary society makes disentanglement from technological dependency increasingly challenging. Excessive digital consumption, characterized by perceiving intelligent technologies as integral parts of life and normalizing social media engagement as routine, adversely affects psychological and mental well-being (Oulasvirta et al., 2012; Andreassen et al., 2017).

This study aimed to develop a scale to measure the problems associated with problematic digital technology usage, along with its causes and consequences. It is anticipated that this scale, employed in research on problematic digital technology usage, will contribute to understanding the underlying psychological mechanisms and aid in developing strategies to mitigate such usage. Moreover, the study's emphasis on fostering balanced and healthy relationships with technology could potentially contribute to strategies that reduce problematic digital technology usage.

The ways individuals interact with digital technologies, from social media platforms to online gaming and the perpetual allure of smartphones, are becoming increasingly complex and problematic. Digital engagement in communication, work, and socialization leads to transformative changes and gives rise to complex issues associated with excessive and compulsive usage (Elhai et al., 2016; Wegmann et al., 2019). Problematic digital technology usage not only affects individual well-being but also disrupts societal fabric. Its consequences extend beyond personal boundaries, influencing interpersonal dynamics, productivity, and the welfare of communities. Digital technology transcends virtual realms, infiltrating physical spaces and profoundly affecting well-being. The interplay between digital and physical lives—from mental fatigue caused by constant connectivity to the physical impact of sedentary screen time—adversely affects physical, psychological, and mental health (Duke & Montag, 2017; Griffiths et al., 2014). Understanding this pervasive phenomenon and its implications is paramount.

This scale development study represents a significant endeavor to confront the challenges of the digital age, raise awareness, promote responsible technology usage, and bridge the gap between virtual and tangible domains in an interconnected world. Enhancing understanding and fostering awareness about problematic digital technology usage is vital.

Literature Review

Problematic Digital Technology Usage and Its Components

Problematic digital technology usage is a multifaceted phenomenon, encompassing dimensions such as loss of impulse control, social isolation, and mental and physical fatigue. In this scale development study, the *University Students' Problematic Digital Technology Usage Scale* was created to understand perceptions of problematic technology usage among university students exposed to varying levels of digital technology. The primary objective was to develop a reliable, valid, and highly representative scale that could offer practical insights for practitioners and policymakers. The scale was designed to be adaptable, reflecting changes in digital behaviors, advancing technologies, and evolving social norms.

The *University Students' Problematic Digital Technology Usage Scale* integrates data from interviews and interactions related to human-digital technology dynamics. This study aims to illuminate the complexities of problematic digital technology usage, contributing to a comprehensive understanding of its underlying causes and consequences. By fostering greater awareness of responsible technology usage, the research seeks to promote a culture of digital mindfulness and accountability. Additionally, the study aspires to safeguard students' well-being and autonomy in the digital era, while simultaneously harnessing technology's transformative potential.

Loss of Impulse Control

Impulses are spontaneous urges or desires often linked to immediate gratification or relief from discomfort. In psychology and human behavior, "impulse control loss" refers to the inability to regulate or resist sudden desires or urges. Individuals experiencing impulse control loss may struggle to avoid engaging in impulsive behaviors, such as making hasty decisions without considering the consequences or feeling unable to resist the urge to use digital technology. Impulse control loss entails a diminished capacity to manage impulses, often leading to harmful or destructive behaviors (Smith & Steel, 2019; Grant & Chamberlain, 2016; Leeman & Potenza, 2012; Verbruggen & Logan, 2009).

When someone experiences loss of impulse control, they may find it difficult to resist acting on impulses, even when the outcomes could be detrimental. This can manifest in various ways, such as impulsive spending, substance addiction, binge eating, reckless driving, aggression, or engaging in risky sexual behaviors. Impulse control loss is a symptom of various mental health conditions, including attention deficit hyperactivity disorder (ADHD), bipolar disorder, borderline personality disorder, and certain neurological conditions (Pontes et al., 2017; Hawi et al., 2019). Additionally, it can be triggered by excessive stress, trauma, or environmental factors.

The causes of impulse control loss vary depending on the context. Some individuals may struggle with impulse regulation due to conditions such as ADHD, impulse control disorders, or specific personality disorders. High levels of stress, emotional distress, or underlying mental health issues can also impair an individual's ability to regulate impulses (Dick et al., 2011; Dick et al., 2010).

Loss of Impulse Control may also result from a lack of planning or consideration of consequences before taking action. In some cases, weakened inhibitory mechanisms impair the ability to stop or control certain behaviors. Impulse control loss can arise when these mechanisms fail to function effectively.

There is evidence suggesting a connection between digital addiction and loss of impulse control. These findings indicate that impulse control loss in the digital realm stems from a combination of psychological and behavioral factors, with individual experiences varying. Increasing reliance on digital tools and the desire to spend more time online to achieve the same level of satisfaction are primary contributors to impulse control loss in the digital domain (Al-Samarraie et al., 2021; Hodkinson, 2019; Wolniewicz et al., 2018; Alt, 2015).

Social media, emails, news, and exaggerated visuals from various digital sources can weaken individuals' ability to control impulses. Excessive digital technology use, such as prolonged gaming, social media consumption, and Internet browsing, often serves as a form of escapism from real-life challenges or responsibilities. These activities can lead to procrastination, as essential tasks are deferred or neglected, diminishing motivation to achieve goals in the physical world (Bari & Robbins, 2013; MacKillop et al., 2016; Casey & Jones, 2010).

Dopamine, a neurotransmitter associated with pleasure and reward, plays a significant role in impulse control loss. Over time, individuals can become dependent on digital stimuli to experience sensations of reward. Exposure to curated and idealized lives on social media platforms, along with the fear of missing out (FOMO), are key factors leading to digital addiction and impulse control loss (Bilkay, 2021; Abel et al., 2016). Social isolation, feelings of overwhelm, and loss of motivation are common consequences of problematic digital technology usage.

Social Isolation

Social isolation occurs when individuals lack meaningful social contact with others. It is characterized by physical separation or limited interactions with family, friends, and the broader community. Social isolation can be both an objective condition, determined by the number of social connections, and a subjective experience, influenced by the perceived quality and depth of these connections. Often manifesting as geographic isolation, it signifies restricted access to social networks and support (Elhai et al., 2016; Elhai et al., 2017).

Social isolation is a significant issue closely linked to social anxiety. It is generally marked by limited social interactions, reduced social networks, emotional detachment, decreased participation in community activities, and limited social support. These conditions are often exacerbated by excessive screen time and other factors, leading to adverse effects on both physical and mental health (Shankar et al., 2017; Rico-Uribe et al., 2016). Excessive digital engagement drives individuals to favor online interactions over face-to-face communication, resulting in heightened social isolation. It also diminishes the desire to participate in real-world activities due to a lack of external motivation, support, and accountability. Social isolation can be either voluntary or involuntary, arising from various factors such as geographic distance, physical disability, mental health challenges, cultural influences, or broader social conditions (Leigh-Hunt et al., 2017; Cornwell & Waite, 2017; Chatterjee & Yap, 2018). Regardless of its origins, addressing social isolation requires a holistic approach that considers the social, emotional, and environmental needs of individuals.

Social isolation is associated with numerous psychosomatic issues, including depression, anxiety, social anxiety disorder, high stress levels, feelings of loneliness, cognitive decline, memory problems, and a weakened immune system.

Problematic digital technology usage stems from compulsive or excessive engagement with digital devices and online platforms, posing a substantial challenge to real-world interactions. Individuals dependent on digital technology often prioritize online interactions over face-to-face communication, leading to diminished real-world social connections. Spending excessive time on social media or gaming platforms can result in neglecting relationships with friends, family, and peers. Another significant consequence of problematic digital technology usage is the deterioration of social skills. Overuse of digital devices hinders the development and maintenance of interpersonal skills vital for meaningful relationships (Shankar et al., 2011; Leigh-Hunt et al., 2017; Valtorta et al., 2016). People who spend excessive time online may struggle to exhibit effective communication, empathy, and the ability to form deep connections in real-life settings.

Problematic digital technology usage also serves as an escape from real-world problems or social difficulties. Screen-dependent individuals may withdraw into the digital realm to avoid confronting social situations that cause discomfort or anxiety, which ultimately leads to increased isolation from peers and society. Distorted social comparisons, driven by glorified content seen online, are another harmful effect of problematic digital technology usage. Social media platforms often showcase idealized portrayals of people's lives, leading to unrealistic social comparisons and feelings of inadequacy (Beutel et al., 2017; Matthews et al., 2019; Leigh-Hunt et al., 2017). These comparisons contribute to decreased self-esteem and reluctance to engage in social relationships, as individuals may feel unable to measure up to the seemingly perfect lives of others.

Physical and Cognitive Fatigue

Physical fatigue resulting from excessive digital technology usage is caused by the prolonged use of digital devices and activities requiring physical participation in technology use. A significant symptom of physical fatigue is eye strain, resulting from extended screen time. Symptoms of eye strain include dry eyes, blurred vision, headaches, and difficulty focusing. The blue light emitted from digital screens disrupts circadian rhythms, contributing to eye discomfort and sleep pattern disturbances (Van Cutsem et al., 2017; Vrijkotte et al., 2018). Digital eye strain presents with tired eyes, headaches, and difficulty concentrating. Furthermore, repetitive movements, such as prolonged typing or using a mouse, can lead to musculoskeletal problems. Other factors contributing to physical fatigue include incorrect posture, poor ergonomics, sleep deprivation, illness, dehydration, or prolonged stress exposure (Vaes et al., 2022; Tasdelen & Özpınar, 2020; Alonso et al., 2016).

Cognitive or mental fatigue refers to a state of mental exhaustion that often accompanies physical fatigue in a digital environment. It occurs when individuals experience mental strain due to constant exposure to information and notifications, along with the cognitive demands of multitasking. Managing data flow in digital environments can lead to cognitive overload, mental fatigue, impaired concentration, and cognitive dysfunction. Multitasking and jobs requiring high mental effort and sustained focus contribute to increased stress and decreased productivity (Alonso et al., 2016; Steege et al., 2015; Kar & Hedge, 2020). Constant accessibility expectations and emotional exhaustion in the digital realm are also significant causes of mental fatigue. The pressure to maintain a positive online presence on social media platforms can lead to feelings of inadequacy, reduced self-esteem, and psychological fatigue (Mujeeb & Zubair, 2021; Xinping et al., 2020; Russell et al., 2019).

Physical and mental fatigue are often interconnected and should be addressed in tandem. Persistent or severe fatigue requires identifying underlying medical or psychological factors (Van Cutsem et al., 2017; Smith et al., 2015). Continuous connectivity in the virtual environment, excessive information overload, and multitasking contribute to both physical and mental fatigue. Psychosomatic problems, particularly sleep disorders, are frequently associated with digital fatigue. Excessive screen time, especially close to bedtime, can disrupt sleep patterns, leading to symptoms such as insomnia, difficulty falling asleep, or disrupted sleep cycles (Khodabakhsh et al., 2021; Jeon & Choi, 2019; Lee et al., 2023).

Cognitive fatigue can also result from prolonged periods of intense mental activity, such as studying for exams, working on complex tasks, or managing excessive information loads. Lack of sleep, stress, and certain medical conditions are additional contributors to cognitive fatigue. Symptoms include difficulty concentrating, memory impairment, decreased mental clarity, slower reaction times, and an increased likelihood of errors (Alimoradi et al., 2019; Tseng et al., 2019; Alonso et al., 2016). While physical and cognitive fatigue have distinct characteristics, they often coexist and influence one another, making it essential to address them comprehensively.

Research Methodology

Scales are data collection tools designed to measure knowledge, emotions, interests, perceptions, attitudes, beliefs, tendencies, risks, quality of life, and behavior (Özdamar, 2017; Kishore et al., 2021). The primary objective of scale development is to create tools that contribute to the generation of scientific knowledge. Observations, interviews, experiments, biophysical measurements, and self-report techniques are commonly employed in scale development and data collection processes. Scales, as self-report data collection tools, facilitate the quick, easy, and standardized collection of research data.

This study aimed to develop the *Problematic Digital Technology Use Scale for University Students: Validity and Reliability Study*. A 52-item, five-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = undecided, 4 = agree, 5 = strongly agree) was developed to measure university students' perceptions of problematic digital technology use. Care was taken to ensure that at least three related items measured the same structure (dimensions/factors) during the scale development process (Carpenter, 2018). After assessing the surface validity of the scale, a pilot study was conducted with a sample group of at least 30 individuals with similar characteristics (Kishore et al., 2021; Gökdemir & Yılmaz, 2023), and data were collected from 140 individuals based on standard sampling rules.

The scope validity of the scale, referring to whether the items represent all aspects of the intended variable and possess sufficient quantity and quality, was evaluated. To ensure this, the opinions of five experts were consulted (Kishore et al., 2021; Karagöz & Bardakçı, 2020). Exploratory Factor Analysis (EFA) was conducted to examine the factor structure of the scale. To ensure a robust factor structure, items with factor loadings below 0.40 or cross-loadings exceeding 0.10 were removed from the scale (Aksu et al., 2016; Tutar & Erdem, 2020). Items with factor loadings between 0.32 and 0.44 were considered weak, those between 0.45 and 0.49 moderate, 0.50 and 0.62 good, 0.63 and 0.70 very good, and 90.71 excellent (Gökdemir & Yılmaz, 2023). The factor loadings for this scale were deemed excellent.

As a result, 34 items were removed based on these criteria, leaving 18 items that formed a three-factor structure. The finalized scale, titled *Problematic Digital Technology Use Scale in Higher Education Students*, comprised these 18 items. For multi-factored scales, it is recommended that they explain at least 40% of the total variance; the scale in this study met this criterion.

A validity and reliability study was conducted by administering the scale to 350 university students. After excluding incomplete or problematic responses, the analysis continued with data from 289 participants. The data were analyzed using the SPSS package, and the 18-item scale's factor structure was re-evaluated through EFA. Confirmatory Factor Analysis (CFA) was conducted using the AMOS package program to validate the three-factor structure obtained from EFA and test the accuracy of the proposed structure.

Population and Sample Group of the Research

The number of participants from whom data will be collected during the research process depends on factors such as the number of items on the scale, researchers' preferences, access to participants, and planned validity and reliability analyses (Kline, 2016; Field, 2018). According to the guideline for determining sample size, items with factor loadings between 0.30 and 0.40 require a sample size of at least 350, while items with factor loadings between 0.40 and 0.50 require at least 200 participants (Gökdemir & Yılmaz, 2023). Based on this rule, a sample of 289 participants was deemed sufficient for this study.

Additionally, it is generally recommended to use a sample size at least five times the number of items on the scale (Boateng et al., 2018; Çokluk et al., 2018; Çapık et al., 2018). In this scale development study, data were collected from 289 participants for the main scale, which met the criteria for an adequate sample size as outlined above.

Participants were recruited from BAU students using a convenience sampling method during the data collection phase of scale development. The demographic indicators of the participants are detailed below.

Findings

This section presents the findings related to the validity and reliability studies of the developed *Problematic Digital Technology Use Scale in Higher Education Students*. Exploratory Factor Analysis (EFA) was conducted to assess the suitability of the dataset for analysis and to determine the factor structure of the scale (Kishore et al., 2021; Gökdemir & Yılmaz, 2023). The results of the Exploratory Factor Analysis (EFA) for the developed scale are presented in Table 2.

Table 1.
Demographic characteristics of the participants

		N	%			N	%
Gender	Male	110	38,1	Marital status	Married	90	31,1
	Female	179	61,9		Single	199	68,9
Age	18-22	89	30,8	Income rate	10.000 ₺ and below	125	43,3
	23-27	111	38,4		10.001-20.000 ₺	108	37,4
	28-32	89	30,8		20.001 ₺ and above	56	19,4
Educational program	Associate Degree	28	9,7	Total Number of Participants = 289			
	Undergraduate	187	64,7				
	Master	37	12,8				
	Doctorate	37	12,8				

Table 2.
EFA Results for the Problematic Digital Technology Use Scale in Higher Education Students

Item No:	New Item No:	Direction	Factor Loadings (Varimax Rotation)			Common Variance	Mean	Standard Deviation	Corrected Item Subscale Total Correlation
			Loss of Impulse Control	Social Isolation	Physical and Mental Fatigue				
32	1	+	,847			,731	3,12	1,39	,669
39	2	+	,809			,725	2,82	1,40	,725
22	3	+	,759			,624	3,38	1,34	,652
23	4	+	,757			,656	2,88	1,42	,731
46	5	+	,742			,603	3,15	1,37	,679
38	6	+	,729			,633	2,97	1,41	,721
31	7	+	,690			,536	3,09	1,36	,654
33	8	+	,611			,423	3,13	1,36	,582
11	9	+		,820		,729	2,09	1,27	,623
12	10	+		,776		,661	1,92	1,18	,617
40	11	+		,736		,658	2,10	1,29	,673
13	12	+		,707		,609	2,21	1,29	,624
35	13	+		,683		,572	2,33	1,34	,636
20	14	+			,880	,833	3,15	1,39	,639
19	15	+			,827	,743	3,04	1,41	,593
18	16	+			,821	,719	3,15	1,38	,580
21	17	+			,615	,546	2,78	1,41	,634
15	18	+			,531	,444	3,16	1,29	,608
Eigenvalues:			7,567	2,381	1,495	KMO: 0,915 Bartlett's Test: 0,000			
% of Variance:			%26,982	%18,746	%17,847	% of Cumulative Variance: %63,575			
Number of Items:			8	5	5	Total Number of Items: 18			
Cronbach's Alpha:			0,907	0,860	0,858	Cronbach's Alpha for Scale: 0,918			

To assess the adequacy of the sample size, the recommended minimum number of participants was determined using anti-image correlation values and the Kaiser-Meyer-Olkin (KMO) coefficient. The Kaiser-Meyer-Olkin (KMO) test results confirmed a sufficient sample size. The KMO value is interpreted as follows: 0.50–0.59 indicates a poor sample size, 0.60–0.69 indicates moderate adequacy, 0.70–0.79 indicates good adequacy, 0.80–0.90 indicates very good adequacy, and >0.90 indicates excellent adequacy (Field, 2018; Seçer, 2018). In this study, the KMO coefficient was 0.915, indicating an excellent sample size.

For the normality condition to be met, the Bartlett Sphericity Test result should be significant ($P < .05$), skewness values of the items should be <3, and kurtosis values should be <10 (Özdamar, 2017; Robinson, 2018). In this study, the Bartlett Test yielded a significance value of 0.000 ($p < 0.05$), indicating that the assumption of multivariate normal distribution of the data was met (Tutar & Erdem, 2020; Coşkun & Mutlu, 2017). This result confirms that the dataset had high correlations between variables and was suitable for factor analysis (Karagöz et al., 2019). Exploratory Factor Analysis (EFA) was applied to the 18-item *Problematic Digital Technology Use Scale for Higher Education Students*, resulting in a three-factor structure.

In scale development studies, the dataset's suitability for analysis should be confirmed, and exploratory factor analysis (EFA) should be conducted to determine the scale's factor structure. According to factor analysis guidelines, single-factor scales should explain at least 30% of the total variance, while multi-factor scales should explain at least 40% of the total variance (Field, 2018; Seçer, 2018; Gökdemir & Yılmaz, 2023). In this study, the total explained variance was 63.575%, which is considered sufficient as it exceeds the 50% threshold.

The internal consistency of Likert-type scales is typically determined using the Cronbach's Alpha Coefficient (α). For a scale to be considered reliable, it is recommended that Cronbach's alpha coefficient (α) be 90.70 for the overall scale and each subscale. For newly developed scales, a value of α 90.60 is considered sufficient. A Cronbach's α value of

Table 3.
Problematic Digital Technology Use Scale in Higher Education Students

Item No:	New Item No:	Items	Sub-Dimensions
32	1	I have a hard time limiting my digital screen time.	Loss of Impulse Control
39	2	I have difficulty controlling my digital device use.	
22	3	I often catch myself wandering in the virtual environment.	
23	4	I have a hard time setting clear boundaries in online browsing.	
46	5	After spending too much time on the internet, I feel meaningless.	
38	6	I feel like I have become addicted to digital devices.	
31	7	I lose work motivation when I spend too much time on the internet.	
33	8	I feel guilty when I spend a long time on digital devices.	
11	9	Staying online for extended periods makes me feel lonely.	Social Isolation
12	10	I have difficulty establishing face-to-face relationships due to being online for long periods.	
40	11	I feel pressure to stay online.	
13	12	Following social media for a long time causes the worry of missing current developments.	
35	13	I worry about missing digital content when I am offline.	
20	14	I sometimes suffer from neck pain due to digital fatigue.	Physical and Mental Fatigue
19	15	I sometimes suffer from back pain due to digital fatigue.	
18	16	I sometimes get headaches due to digital fatigue.	
21	17	I experience hand and arm numbness due to being online for a long time.	
15	18	The internet's information overload causes me to become mentally exhausted.	

α 90.90 indicates excellent internal consistency, 0.70 4 α < 0.90 indicates good consistency, 0.60 4 α < 0.70 indicates acceptable consistency, 0.50 4 α < 0.60 indicates poor consistency, and α < 0.50 is deemed unacceptable (Field, 2018; Seçer, 2018; Gökdemir & Yılmaz, 2023; Kalaycı, 2010; İpek & Mutlu, 2022).

A reliability analysis of the 18-item scale administered to participants was conducted, and the Cronbach's alpha coefficient was found to be 0.918. This result indicates a very high level of internal consistency for the scale.

Results of Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted to validate the three-factor structure obtained from the Exploratory Factor Analysis (EFA) results and test the accuracy of the identified structure. In the first-level CFA, when examining the Path Diagram, standardized solution values (factor loadings) should be at least 0.30, preferably 0.50. The error variances of the items should be at most 0.90, and all t-values should be significant. When determining the level of fit between the model and data, multiple model fit indices were examined, and the χ^2/df ratio was considered. If χ^2/df42, the model fit is excellent; if 3<χ^2/df45, the model fit is considered acceptable (Gökdemir & Yılmaz, 2023; Seçer, 2019; Orçan, 2018). For Confirmatory Factor Analysis, at least three variables should measure each latent variable (Kalaycı, 2010). The following fit indices are generally used to evaluate the CFA model fit (Karagöz et al., 2019):

Chi-Square Statistic (χ^2) to Degrees of Freedom (df) Ratio: This statistic evaluates the model's fit to actual data. However, this statistic can be significant depending on the sample size; therefore, it should be evaluated with other indices. In general, it is expected to be less than 5.

The fit Indices (CFI, GFI, AGFI, NFI, and IFI) take values between 0 and 1. The closer these values are to 1, the better the model fit. Typically, values above 0.90 are desirable. CFI values 990 indicated acceptable fit and 995 indicated excellent fit. As CFI approaches 1.00, and RMSEA and SRMR approach zero, model fit also improves (Gökdemir & Yılmaz, 2023).

RMSEA (Root et al. of Approximation): This takes a value between 0 and 1. The closer it is to 0, the better the fit of the model. Generally, being less than 0.08 is considered acceptable. In the analyses, if RMSEA 40.05, the model fit was excellent, 0.05-0.08 was acceptable, 0.08-0.10 was poor, and >0.10 was unacceptable (Gökdemir & Yılmaz, 2023). A diagram of the model fit is shown in Figure 1.

As a result of the analyses, it was seen that all standardized path coefficients had values greater than 0.5 (Gökdemir & Yılmaz, 2023). Additionally, the covariances between the factors are pretty significant and all positive, as expected. Fit index values and beta coefficient statistics are given in Table 4 below.

Regression values indicate the ability to predict the latent variables of the observed variables, that is, factor loadings. The factor loadings are statistically significant since the "p" values for each pair of relationships above are less than 0.001. This indicates that the items loaded onto the factors. Additionally, standardized regression coefficients of 0.500 and above indicate a high ability to predict latent variables, indicating that the factor loadings of each item are strong (Karagöz et al., 2019). Table 4 shows that the fit values obtained adequately represented the model fit. The results of Confirmatory Factor Analysis (CFA) confirm the validity of the sub-factors obtained from Exploratory Factor Analysis (EFA) is confirmed.

Figure 1.
Standardized Values for the Problematic Digital Technology Use Scale in University Students

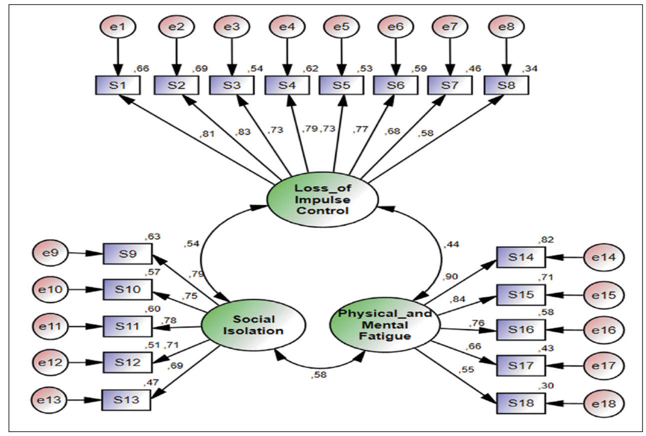

Table 4.
Confirmatory Factor Analysis (CFA) Results

Items		Sub-Dimensions	B	Std. B	S.H.	t	Sig.
S4	⟵	Loss of Impulse Control	,996	,789	,066	15,059	0,000
S3	⟵	Loss of Impulse Control	,872	,733	,064	13,659	0,000
S6	⟵	Loss of Impulse Control	,958	,767	,066	14,495	0,000
S1	⟵	Loss of Impulse Control	1,000	,811	-	-	-
S11	⟵	Social Isolation	,994	,777	,073	13,562	0,000
S13	⟵	Social Isolation	,908	,686	,077	11,753	0,000
S9	⟵	Social Isolation	1,000	,793	-	-	-
S2	⟵	Loss of Impulse Control	1,034	,832	,064	16,202	0,000
S5	⟵	Loss of Impulse Control	,882	,729	,065	13,546	0,000
S7	⟵	Loss of Impulse Control	,817	,680	,066	12,392	0,000
S8	⟵	Loss of Impulse Control	,703	,583	,068	10,291	0,000
S14	⟵	Physical and Mental Fatigue	1,000	,903	-	-	-
S15	⟵	Physical and Mental Fatigue	,948	,840	,051	18,452	0,000
S16	⟵	Physical and Mental Fatigue	,838	,762	,053	15,778	0,000
S17	⟵	Physical and Mental Fatigue	,736	,655	,058	12,600	0,000
S18	⟵	Physical and Mental Fatigue	,565	,550	,057	9,989	0,000
S12	⟵	Social Isolation	,910	,712	,074	12,276	0,000
S10	⟵	Social Isolation	,878	,752	,067	13,063	0,000
		(132)=325,298	RMSEA=0,071 < 0,08			CFI=0,932 > 0,90	
		=2,464 < 3	AGFI=0,906 > 0,90			GFI=0,908 > 0,90	
		p=0,000	NFI=0,901 > 0,90			IFI=0,932 > 0,90	

Discussion and Conclusion

This study aimed to develop the *Problematic Digital Technology Use Scale for Higher Education Students* and evaluate whether the scale has a valid and reliable structure. A comprehensive literature review was conducted, and discussions with experts were held to identify the dimensions, structure, components, and conceptual framework of the phenomenon to be measured (Kishore et al., 2021; McKim, 2022). Both deductive and inductive approaches were employed in developing the scale items. The deductive approach involved a thorough literature review, while the inductive approach utilized observation and interview techniques to gather data from the target population.

Initially, a detailed literature review was conducted, resulting in the creation of a 52-item draft scale. Experts reviewed and approved the scope and surface validity of the items (Morgado et al., 2017). The draft measurement tool was then administered to 144 participants in a pilot study. Statistical analyses indicated that the sample size was sufficient and that factor analysis was feasible. Following Exploratory Factor Analysis (EFA), 34 statistically insignificant or inconsistent items were removed from the scale, resulting in an 18-item scale with three factors. The revised scale was subsequently tested for validity and reliability with 289 participants. The results confirmed that the three-factor structure of the *Problematic Digital Technology Use Scale for University Students* was preserved, with each factor appropriately labeled based on the items grouped under it.

The first eight items of the scale were grouped under the first factor, labeled "Loss of Impulse Control." The next five items were grouped under the second factor, labeled "Social Isolation." The final five items were grouped under the third factor, labeled "Physical and Mental Exhaustion." Reliability analyses indicated a high degree of reliability. Confirmatory Factor Analysis (CFA) was conducted to confirm the validity of the three-factor structure and to test the accuracy of the identified model. The fit indices obtained adequately represented the model fit, confirming the structural validity of the scale. High values of standardized path coefficients and positive covariances between factors highlighted strong relationships among the scale's factors.

The findings demonstrate that the *Problematic Digital Technology Use Scale for University Students*, consisting of three factors and 18 items, is a reliable, valid, and structurally appropriate measurement tool. This scale comprehensively assesses problematic digital technology use and is a reliable tool for academic and applied research.

Although some scale development studies related to this area exist in the national literature, none provides a tool with such a broad framework for measuring digital fatigue across multiple dimensions. For example, the scale developed by Türen et al. (2015), titled *Techno-Stress Scale in the Workplace: A Study in the Aviation and Banking Sectors*, measures technostress levels but lacks comprehensive coverage for assessing digital fatigue. Similarly, the study by Çoklar et al. (2023), *Defining Teachers' Technostress Levels: A Scale Development*, focuses solely on measuring teachers' technostress levels. The scale developed by Bulut et al. (2023), *Psychometric Properties of the Turkish Version of the Technostressors Scale for Health Professionals*, may have limitations in cultural adaptation and content breadth compared to this scale. Additionally, the study by Baş et al. (2021), titled *Adaptation of the Technostress Levels Scale in a Technology-Enhanced Learning Environment for University Students: Validity-Reliability Study*, differs significantly in terms of cultural adaptation, scope, and content, as it is limited to learning environments.

This scale is a functional tool with demonstrated reliability and internal consistency, making it valuable for researchers and practitioners. Researchers can use it to identify the causes and consequences of problematic digital technology use, while practitioners and educators can utilize it to raise awareness among students about the implications of such usage. Although this study lays the groundwork for understanding problematic digital technology use, further research is recommended to explore the scale's applicability in diverse contexts and populations. Longitudinal studies may provide insights into the temporal dynamics of problematic digital technology use, offering a deeper understanding of this evolving phenomenon.

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