Psychiatric Quarterly
https://doi.org/10.1007/s11126-025-10220-z

ORIGINAL PAPER

Development and Psychometric Analysis of the Digital Detox Scale

Aslı Akdeniz Kudubeş[1] · Özkan Özbay[2] · Metin Beşaltı[3] · Sevil Çınar Özbay[4] · Selma Durmuş Sarıkahya[5]

Received: 2 August 2025 / Accepted: 6 September 2025

Abstract
The widespread use of digital technologies keeps individuals constantly online, which may increase the risk of digital addiction. Digital detox, defined as the conscious limitation of technology use, has emerged as a strategy to achieve healthier balance. This study aimed to develop and validate a scale to measure university students' digital detox levels. Designed as a cross-sectional methodological study, it was conducted with 701 students at a university in Türkiye. Scale development followed established procedures, including item generation, expert review, and psychometric evaluation. Analyses supported a multidimensional, 27-item structure with strong evidence of reliability and validity. The scale provides a practical tool for assessing digital detox levels among university students and can be applied in academic and clinical contexts to evaluate technology-use habits and support strategies for balanced digital engagement.

Keywords Digital detox · University students · Scale development · Reliability · Validity

Introduction

The rapid expansion of information technologies and the widespread integration of digital devices into all aspects of life have led individuals to remain constantly online in both their professional and social lives [1]. The engaging designs of social media and digital entertainment platforms encourage individuals to spend their leisure time in digital environments as well [2, 3]. This constant digital exposure has prompted individuals to seek a more balanced lifestyle over time [4]. Various strategies, such as taking breaks from smartphone use, setting time and space limitations on digital devices, and deactivating social media accounts, have become widely adopted to achieve this balance [5–10]. Among these strategies, one of the most well-known is the practice of "digital detox", which involves taking a break from digital devices and online activities to reduce stress and improve overall well-being [11–14].

Extended author information available on the last page of the article

Although the concept of digital detox has been around for about a decade, its popularity has grown rapidly in recent years as more people recognize the benefits of disconnecting from digital devices to improve mental health and overall well-being [9]. In the literature, this concept is referred to by various terms such as detox, break, disconnection, unplugging, or digital cleansing, but the most commonly used term is “digital detox.” Digital detox refers to consciously refraining from all digital activities (such as smartphone and social media use) for a specific period (e.g., an hour, a day, or longer) [10]. Digital detox is a period of time when a person does not use digital devices such as smartphones or computers, especially in order to reduce stress and relax [15]. Digital detox is often associated with trends such as “disconnecting” or “pushing back against technology.” This process involves limiting digital device usage during activities such as studying or having dinner to improve focus, strengthen social interactions, and support a healthier balance between digital and real-life experiences [16–19].

Schmuck [10] investigated the effectiveness of digital detox applications in reducing problematic smartphone use and improving the mental well-being of young adults. The research involved 500 participants and a high proportion (41.7%) of young adults engaged in digital detox applications. Among individuals who do not use digital detox apps, social networking site usage is positively associated with problematic smartphone use and negatively associated with well-being. Therefore, digital detox practices are considered a valuable tool for mitigating the harmful effects of social network usage on youth well-being by reducing the risk of problematic smartphone use. In a study by Albayrak [20], university students deactivated their social media accounts for one week. After this digital detox, positive changes were observed in productivity, creativity, and family communication. Additionally, studies have found that restricting email responses to specific hours can reduce workplace stress [21]. Zahariades [22] summarized the benefits of digital detox, noting improvements in productivity, social relationships, stress reduction, sleep quality, focus, self-discipline, creativity, and memory. These findings suggest that digital detox strategies can positively impact overall well-being. Experts frequently emphasize the importance of digital detox in seminars on healthy living, stress management, and work-life balance, highlighting its growing necessity [9].

Digital detox offers boundary-setting and cleansing strategies to help individuals maintain their physical and mental health, communication skills, and productivity [23]. By promoting more mindful media consumption habits, these strategies enable individuals to mitigate the risks of digital addiction and regain control over their screen time [13]. However, despite its growing popularity, the concept of digital detox remains ambiguous in the literature, with ongoing debates about its effectiveness and long-term impact [9].

Research investigating the effects of digital detox on individual well-being has yielded mixed results, highlighting a gap in the existing literature [10, 14, 24]. While some studies suggest that periodic breaks from digital technologies can have a positive impact on mental health and overall life satisfaction [24–26], others suggest that digital detox has no measurable benefits, raising the question of its benefits [27–29]. The lack of clarity regarding the effects of digital detox further complicates efforts to assess its true impact, emphasizing the need for more comprehensive research in this area [9, 10].

Further research is needed to clarify the benefits of digital detox by examining factors such as optimal detox duration, severity of phone addiction, and technology-related stress. A deeper understanding of these elements can help determine whether digital detox is a truly effective strategy for improving well-being. Adopting a balanced approach to technology use is essential for preventing technology addiction. This involves ensuring more controlled, conscious, and intentional engagement with digital devices, rather than resorting to extreme disconnection [9]. Changing digital consumption habits with the mindset that "less is more" can be a significant step toward mindful media use [9, 14, 23]. By integrating moderation and self-awareness into daily digital interactions, individuals can create sustainable habits that support both productivity and well-being.

Theoretical Background: Digital Detox Framework

Although digital detox has gained popularity as a strategy to mitigate the adverse effects of constant digital engagement, the concept still suffers from limited conceptual and theoretical clarity. Much of the existing literature relies on descriptive or experience-based interpretations rather than grounding the phenomenon in established theoretical frameworks. Addressing this gap, a comprehensive belief–action–outcome model was proposed that conceptualizes digital detox as a self-regulatory response to perceived digital overuse. This framework offers a structured lens to understand how beliefs about excessive technology use drive behavioral interventions such as setting boundaries or abstaining from digital devices, which ultimately influence psychological and behavioral outcomes [30]. Moreover, the framework highlights the importance of aligning detox strategies with users' internal motivations and contextual factors to ensure both conceptual coherence and empirical validity.

Complementing this perspective, Syvertsen [13] categorized digital detox practices into two principal domains: behavioral change and the management of technological devices. These strategies aim to help individuals cope with the distractions and psychological strain caused by continuous digital connectivity. However, successfully adopting digital detox practices can be difficult, particularly for those who are highly dependent on digital technologies in their daily lives. It is therefore crucial to frame digital detox not as a temporary rejection of technology, but as a long-term approach to enhancing personal well-being, fostering intentional technology use, and promoting healthier digital habits.

To support a more systematic understanding of digital detox, Forster et al. [31] conducted a structured literature review and identified eight core thematic clusters in empirical research: behavioral change, experience, health, motivation, stress perception, social interaction, strategy, and work-related impacts. These findings underscore the multidimensional nature of digital detox and the need for measurement tools that can effectively capture its personal, behavioral, and contextual complexities. In response, the present study developed a Digital Detox Scale (DDS) structured around six theoretically informed subdimensions: health, managing digital device use, digital content consumption, limiting digital device use, digital device use habits, and social interactions. These subscales were carefully designed to reflect the thematic clusters identified in prior literature and provide comprehensive coverage of the behavioral domains associated with digital detox.

Despite growing empirical interest in digital detox, measurement approaches in the literature often lack standardization and psychometric robustness. Hager et al. [32] highlighted this issue in their systematic analysis of 65 studies, calling for the development of valid, reliable instruments that can assess digital detox behaviors, intentions, and outcomes across various populations and settings. Guided by these insights, the current study adopts a theory-driven approach to scale development, ensuring that item construction and factor structuring are firmly rooted in both conceptual frameworks and empirical themes.

In summary, the integration of these theoretical and empirical insights provides a robust foundation for the development of the DDS. Anchored in the belief–action–outcome model and mapped to empirically supported dimensions, the DDS contributes to advancing the theoretical understanding of digital detox while offering a reliable tool for both academic research and practical applications (Fig. 1). Moreover, it serves as a useful instrument for individuals aiming to manage their technology use more consciously and effectively, ultimately supporting broader efforts to prevent and reduce digital overuse and addiction.

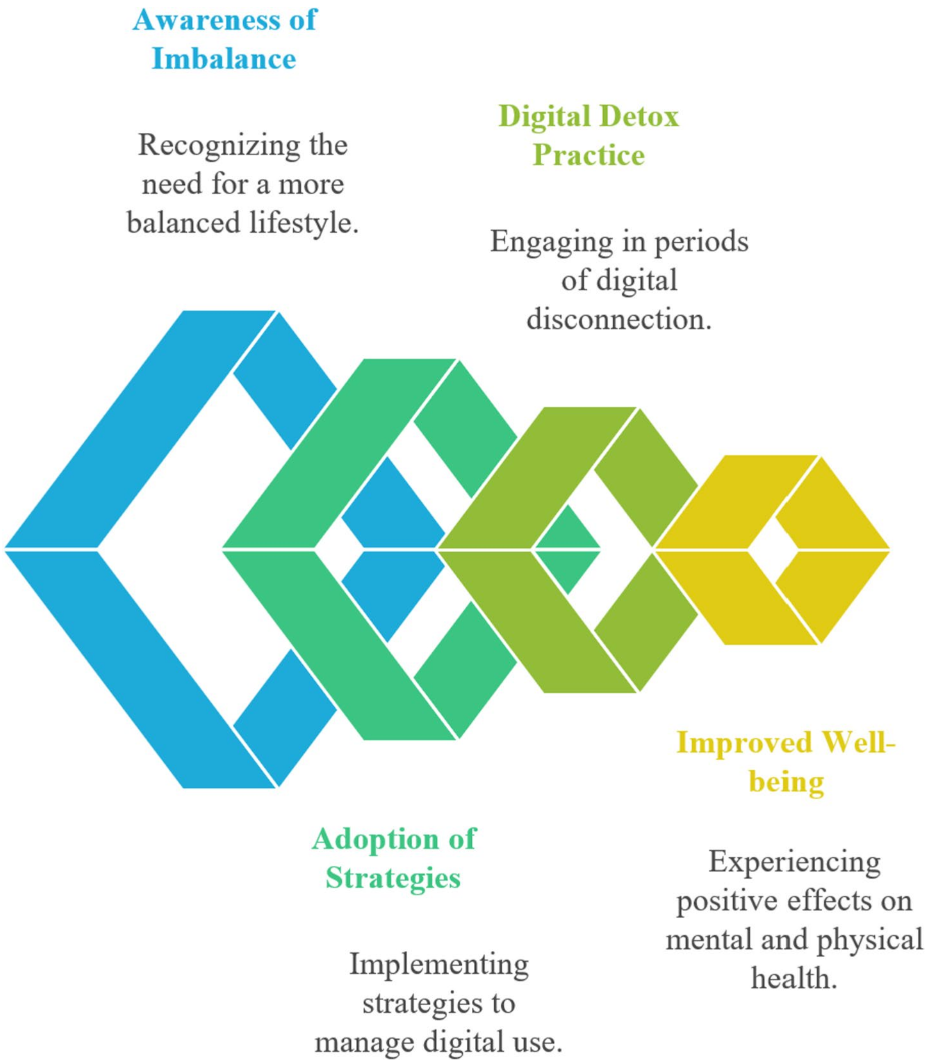

Fig. 1 Digital detox process

Method

Research Design

This cross-sectional and methodological study aims to develop a DDS to measure university students' digital detox levels and examine its psychometric properties.

Participants

The participants of the study consisted of students with experience in using digital devices who voluntarily agreed to participate and were selected through purposive sampling from a university in Türkiye during the Fall semester of the 2024–2025 academic year. Purposive sampling is a deliberate method that allows researchers to focus on a specific subgroup or population of interest [33]. Specifically, when the research targets a particular group, this method allows for more comprehensive and accurate results [34]. In this study, university students who use digital devices were targeted, and purposive sampling was applied. The study selected participants from various faculties of the university. Informed consent was obtained from all participants before the data collection process. Data were collected through a face-to-face survey method.

Scale development studies recommend three basic rules for sample size calculation: the 5 s, 10 s, and 100 s rules. It is stated that there should be at least five participants per item for factor analysis to be conducted. If the sample size is sufficient, it is emphasized that there should be 10 participants per item [35]. Additionally, it is recommended to conduct exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) on different datasets during the scale development process [36]. In this case, 660 people were needed for both the EFA and CFA to study the validity and reliability of the DDS, which has 33 items and 10 participants for each item. However, this study reached a total of 701 students.

Data Collection Instruments

Personal Information Form This form was prepared by the researchers to determine students' personal information, such as age and gender, as well as their smartphone usage habits. The form includes questions about daily smartphone usage time, internet usage time, and whether the smartphone is turned off at night while sleeping.

Digital Detox Scale and Development Process

Framework and Item Development

This framework was developed through an extensive literature review using databases such as PubMed, CINAHL, Cochrane Library, Scopus, and Web of Science. The keywords used in the literature search were "digital disconnection," "digital diet," "digital detoxification," "digital self-regulation," and "digital minimalism." The review focused on identifying measurable components and theoretical models that could guide the development of the scale. Based on the literature, the initial theoretical structure of the scale was created, and an item pool consisting of 33 items was prepared.

The trial scale was sent to 15 experts for evaluation of its language and content validity. Based on expert feedback, 3 items were removed from the scale: "I use my digital devices (smartphone, tablet, computer, etc.) at specific times during the day" (I-1), "I limit my social media use to a certain amount of time each day" (I-2), and "I use digital devices within a specified time frame" (I-5).

To determine the construct validity of the Digital Detox Scale, EFA was performed, and three items with factor loadings below 0.35 were removed from the scale. The items removed due to factor loadings under 0.35 were "I avoid using digital devices in social activities" (I-19), "I use my smartphone on silent mode" (I-27), and "I try to limit the time I spend on the internet/social media" (I-30). The scale was evaluated using a five-point Likert scale: Strongly agree = 1 point, agree = 2 points, neutral = 3 points, disagree = 4 points, and strongly disagree = 5 points.

The scale consists of six subscales: health, managing digital device use, digital content consumption, limiting digital device use, digital device use habits, and social interactions. Item 16 in the digital content consumption subscale was reverse-coded. The total score range of the scale is between 27 and 135 points. Subscale scoring is calculated similarly to the total score. Higher scale scores indicate higher levels of digital detox among students.

Specialist Opinions

To ensure the scale's content validity, it is recommended to gather feedback from at least 10 experts [37]. In this study, feedback was obtained from 15 experts from diverse fields such as health sciences, computer science, and educational technologies. Davis's technique was used to evaluate the expert feedback. Experts assessed the relevance and clarity of the scale items using a four-point scale: 1 = not suitable, 2 = somewhat suitable, 3 = suitable, and 4 = very suitable. The Content Validity Index (CVI) was calculated by dividing the number of experts who marked "3" and "4" by the total number of experts. Davis [38] set the minimum acceptable value for the CVI at 0.80.

Pilot Study

A pilot study was conducted with 40 university students who met the inclusion criteria but were not included in the main sample. The students who participated in the pilot study found the scale items to be clear and easy to understand, and no negative feedback was reported. To ensure the validity of the findings, these students were not included in the main sample. After completing the pilot study, we applied the 33-item scale to the main sample and conducted validity and reliability analyses to assess its effectiveness and consistency.

Statistical Analysis

IBM SPSS 22.0 (Chicago, IL) and IBM AMOS 25.0 software were used for data analysis. Categorical data were presented as frequency and percentage, while continuous variables were summarized with mean and standard deviation. The normality of the data was assessed using the Kolmogorov-Smirnov test. The DAVIS method was applied to determine the suitability of the scale items based on expert opinions. The relationships between the item scores obtained from the scale and subscales were examined using Pearson correlation analysis. Internal consistency reliability was tested using Cronbach's alpha coefficient. EFA was conducted to examine the factor structures, and the varimax rotation technique was used in this analysis. EFA was performed using the Varimax rotation method. The negative factor loadings are due to the relative signs, and absolute values were taken into account in interpretation. CFA was carried out through IBM AMOS 25.0. The data set was split into two; EFA was applied to the first half ($n=351$), and CFA was applied to the second half ($n=350$). All analyses were conducted at a 95% confidence level, with a significance level set at $p=0.05$.

Results

It was determined that the mean age of the university students was 20.83 + 2.60 years. The study revealed that 65% of the participants were female, while 35% were male. The academic grade point mean of the participants in the last semester was 1.97 + 1.35, the daily smartphone usage time was 5.46 + 2.82, and the number of computers/tablets/smartphones in their homes was 2.55 + 0.71. Table 1 presents the characteristics of the participants.

Results of Validity Analysis

The first version of the scale consisted of 33 items, and the first version was sent to 15 experts. After expert opinions, 3 items were removed. As a result of the exploratory factor analysis, 3 items with factor loadings below 0.35 were removed from the scale. The final version of the scale was arranged and consisted of 27 items. The agreement among experts ranged from 0.93 to 1.00 for each item (I-CVI) and 0.99 for the whole scale (S-CVI).

EFA results using the Varimax rotation method revealed the scale structure with six sub-scales. Table 2 presents the scale's EFA results. Factor analysis revealed the KMO coefficient was 0.858, the Bartlett test X2 value was 3855.335, and $p<0.001$. The first subscale accounted for 14.98% of the total variance, the second subscale accounted for 14.37%, the third subscale accounted for 9.36%, the fourth subscale accounted for 8.81%, the fifth subscale accounted for 6.83%, and the sixth subscale accounted for 5.61%, for a total of 59.98% of the total variance. The factor loading ranged from 0.634 to 0.841 for the first subscale, 0.601 to 0.821 for the second subscale, 0.556 to 0.685 for the third subscale, 0.422 to 0.831 for the fourth subscale, 0.533 to 0.704 for the fifth subscale, and 0.414 to 0.687 for the sixth subscale (Table 2).

Confirmatory factor analysis confirmed the scale's six-dimensional structure. Table 3; Fig. 2 present the scale's confirmatory factor analysis results.

Results of Reliability Analysis

Table 4 presents the total and sub-scale Cronbach's alpha coefficient results of the scale. The total Cronbach's alpha value of the scale was found to be 0.885. The sub-scale of the scale yielded Cronbach's alpha values of 0.883, 0.844, 0.710, 0.765, 0.610, and 0.667, respectively. Also, Pearson correlation analysis was used to find the item-subscale total score correlations and the correlations between the items and the total score. The results are shown in Table 4.

Table 1 Characteristics of participants ($n=701$)

			Mean ± SD	Min-Max
Age (years)			20.83 ± 2.60	17–42
Academic grade point average in the last semester			1.97 ± 1.35	0–4
How long he has been using a smartphone			6.69 ± 2.97	1–15
Daily smartphone usage time			5.46 ± 2.82	1–10
Number of computers/tablets/smartphones at home			2.55 ± 0.71	1–3
			n	**%**
Gender		Woman	456	65
		Man	245	35
Class		First	202	28.8
		Second	199	28.4
		Third	181	25.8
		Fourth	119	17.0
Family income level		Low	83	11.8
		Middle	594	84.7
		High	24	3.4
Level of use of information technologies (smartphones, computers, tablets, etc.)		Low	34	4.9
		Middle	424	60.5
		High	243	34.7
Intended use of smartphone*	Educational	Yes	223	31.8
		No	478	68.2
	Contact	Yes	109	15.5
		No	592	84.5
	Social media	Yes	102	14.6
		No	599	85.4
	Entertainment	Yes	268	38.2
		No	433	61.8
How to turn off the smartphone at bedtime		Yes	174	24.8
		No	527	75.2
Social media accounts used *	Twitter/X	Yes	358	51.1
		No	343	48.9
	Facebook	Yes	122	17.4
		No	579	82.6
	Instagram	Yes	649	92.6
		No	52	7.4
	Whatsapp	Yes	679	96.9
		No	22	3.1
	Tiktok	Yes	216	30.8
		No	485	69.2
	Youtube	Yes	502	71.6
		No	199	28.4
Daily time spent online		Less than an hour	14	2.0
		One to three hours	240	64.2
		More than three hours	447	63.8
Do you think smartphone use affects your daily life?		Mostly affects	335	50.6
		Rarely affects	303	43.2
		Does not affect	43	6.1

*More than one option was selected by the participants

Table 2 Results of 'exploratory factor analysis (n=351)

Items	Subscales					
	1	2	3	4	5	6
HEALTH						
1. Avoiding the use of digital devices before sleep improves my sleep quality.	0.634					
2. Reducing the use of digital devices lowers my stress levels.	0.746					
3. When I stop using digital devices, my physical pain (such as neck pain, back pain, headaches, eye pain, etc.) decreases.	0.798					
4. When I use digital devices less, the feeling of fatigue in my eyes decreases.	0.831					
5. When I stay away from digital devices, my distraction decreases.	0.841					
6. When I stay away from digital devices, my overall mood changes positively.	0.765					
MANAGING DIGITAL DEVICE USAGE						
7. I do not install social media applications on my digital device.		0.601				
8. I plan the usage time of my social media accounts.		0.789				
9. I limit the usage time of my social media accounts.		0.821				
10. I take a break from social media/I restrict access to social media.		0.775				
11. I use mobile applications that restrict or control device usage.		0.805				
12. I use applications that show how much time I spend on each platform.		0.661				
DIGITAL CONTENT CONSUMPTON						
13. I join groups where I interact with people (sports, culture, arts, etc.).			0.626			
14. I engage in new hobbies, activities, or interests.			0.678			
15. I avoid excessive content consumption on digital devices without time limits.			0.556			
16. I use social media for entertainment.			0.642			
17. I use social media primarily to gain knowledge.			0.685			
LIMITING DIGITAL DEVICE USAGE						
18. I stay away from digital devices that I do not use for work purposes while working.				0.442		
19. I turn off all notifications on my smartphone.				0.801		
20. I mute all notifications on my smartphone.				0.831		
21. I do not use digital devices unless necessary.				0.598		
DIGITAL DEVICE USAGE HABIT						
22. I feel more at peace when I am not using digital devices.					0.669	
23. I regularly stay away from my digital devices to spend time offline.					0.704	
24. I do not use my digital devices during my daily routines (such as cooking/eating, sitting in a café, or waiting in line).					0.533	
SOCIAL INTERACTIONS						
25. I check my phone first thing when I wake up.						0.515

Table 2 (continued)

Items	Subscales					
	1	2	3	4	5	6
26. I prefer face-to-face communication over digital communication in social settings (such as gatherings with friends, events, and family meetings).						0.687
27. I make an effort not to use my digital devices when people are around me.						0.414
Explained Variance (%)	14.98	14.37	9.36	8.81	6.83	5.61
Total Explained Variance (%)	59.98					
KMO Coefficient	0.858					
Barlett Test	3855.335; $p<0.001$					

KMO: Kaiser−Meyer Olkin coefficient

Table 3 Model fit indices of the scale ($n=350$)

	X^2	DF[a]	X^2/DF	RMSEA[b]	GFI[c]	CFI[d]	IFI[e]	RFI[f]	NFI[g]	TLI[h]
Sixth Factor Model	836.627	309	2.708	0.070	0.90	0.90	0.90	0.90	0.90	0.90

a: Degree of Free; b: Root Mean Square Error of Approximation; c: Goodness of Fit Index; d: Comparative Fit Index; e: Incremental Fit Index; f: Relative Fit Index; g: Normed Fit Index; TLI (NNFI): Trucker−lewıs Index

Discussion

Although digital detox has gained popularity as a strategy to reduce the negative consequences of excessive digital engagement, its conceptual clarity and theoretical foundation remain limited in the literature. Much of the existing research tends to focus on anecdotal outcomes rather than structured models. Addressing this gap, a belief–action–outcome framework was proposed that views digital detox as a self-regulatory process influenced by individuals' beliefs about digital overuse [30]. This model emphasizes the importance of aligning detox behaviors, such as limiting screen time or abstaining from digital content, with users' intrinsic motivations and contextual realities. Similarly, Syvertsen and Enli [13] identified two primary domains of digital detox practices: behavioral change and device management. These approaches aim to reduce psychological strain by fostering intentional technology use rather than complete disconnection. The present study contributes to this growing theoretical foundation by developing the DDS in line with these frameworks, offering a structured and psychometrically sound tool to evaluate the multifaceted nature of digital detox behavior among university students.

In the scale development process, an item pool was created to comprehensively address digital detox. The scale items were developed based on individuals' skills in limiting digital device usage, strategies for regulating digital content consumption habits, and attitudes toward prioritizing social interactions. In line with the information obtained from the literature, the focus was placed on strategies to balance the negative effects of excessive digital device usage on individuals [10, 13, 23]. To make the scale items more valid and useful, 15 experts from different fields, such as health sciences, computer science, and educational technology, used the Davis technique to check the items' content validity. However, three items that had a content validity index below 0.8 were removed from the scale [38]. Subsequently, a pilot implementation was conducted with a group of 40

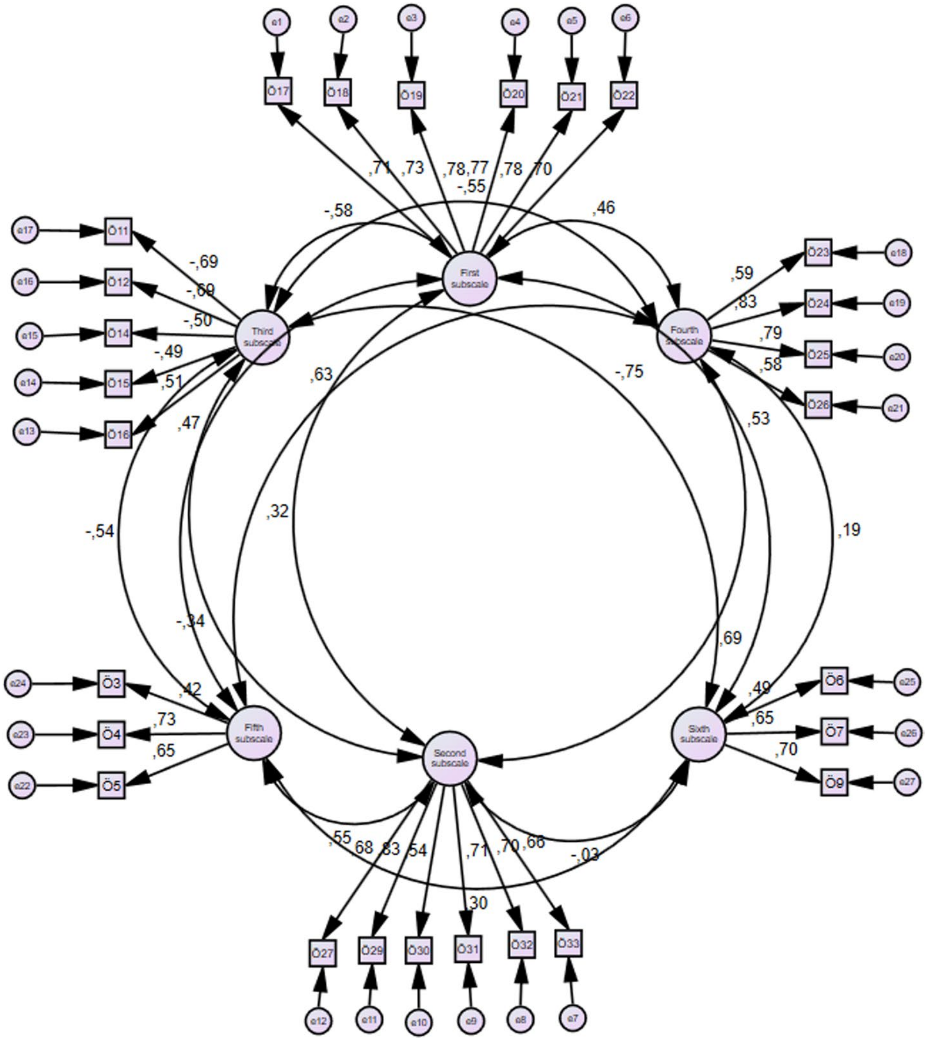

Fig. 2 Results of confirmatory factor analysis ($n=350$)

students to assess the accuracy of the statements and the clarity of the questions. The pilot implementation results showed that the statements were lucid and comprehensible, and no modifications were considered necessary.

To evaluate the construct validity of the scale, an EFA was initially conducted. Before performing factor analysis, certain assumptions need to be tested. In this context, the KMO test and Bartlett's test were applied. The KMO test evaluates the adequacy of the sample size, while Bartlett's examination reveals the correlation between variables [39]. For the Digital Detox Scale, the KMO value was found to be >0.80, indicating that the research sample was sufficient. Furthermore, Bartlett's test was found to be statistically significant, confirming that there was a correlation among the scale items.

Table 4 Results of the reliability analyses of the scale and correlations of the item total score and sub-dimension total score (n=701)

Items	Cronbachα	X±SD	Item-Total Score Correlation	Item-Subscale Total Score Correlation
1	0.883	3.36±1.18	0.533	0.626
2		3.41±1.12	0.583	0.698
3		3.38±1.15	0.542	0.723
4		3.47±1.15	0.526	0.719
5		3.44±1.13	0.584	0.735
6		3.38±1.18	0.579	0.666
7	0.844	2.54±1.21	0.442	0.565
8		2.86±1.18	0.569	0.747
9		2.92±1.58	0.411	0.578
10		2.95±1.13	0.565	0.660
11		2.83±1.20	0.500	0.669
12		2.91±1.24	0.481	0.578
13	0.710	3.47±1.06	0.439	0.523
14		3.48±1.06	0.494	0.529
15		3.09±1.06	0.496	0.407
16		3.56±0.99	0.302	0.418
17		3.39±1.00	0.444	0.458
18	0.765	3.24±1.13	0.555	0.470
19		2.79±1.20	0.525	0.671
20		2.89±1.19	0.531	0.654
21		3.00±1.16	0.522	0.474
22	0.610	2.99±1.11	0.420	0.379
23		2.91±1.09	0.489	0.485
24		2.76±1.18	0.436	0.398
25	0.667	3.29±1.24	0.325	0.322
26		3.30±1.34	0.335	0.406
27		3.63±1.19	0.361	0.408
Total Cronbach Alpha (α) Value				0.885

SD: Standard deviation; X: Mean

EFA evaluated the results from the scale during the data collection process. The factor analysis revealed that the scale consists of six factors. The EFA showed that the scale explained 59.98% of the total variance. According to Kline [40], an explained variance between 40% and 60% is considered sufficient. This finding suggests that the developed scale is acceptable in terms of the explained variance. In this context, the scale was deemed adequate. To explain a structure, factor loadings are classified as high (0.70), moderate (0.50), and low (0.35) to show the relationship of each variable [41]. In this study, three items with factor loadings below 0.35 ("I avoid using digital devices during social activities," "I use my smartphone on silent mode," and "I make an effort to limit my time spent on the internet/social media") were removed from the scale. The EFA revealed that the factor loadings ranged from 0.41 to 0.84, indicating that the items had moderate to high adequacy. As a result, the scale structure obtained from the exploratory factor analysis included six subdimensions: health, management of digital device use, digital content consumption, limiting digital device use, digital device usage habits, and social interactions.

CFA was used to make sure the proposed structure was correct, and fit indices like χ^2/df, GFI, AGFI, CFI, IFI, and RMSEA were used to look at the structure of the draft scale. If the values of CFI, IFI, RFI, NFI, and TLI are higher than 0.90, it means that the model fits well [42]. Fit indices are derived, evaluated together, and closely related values [43, 44]. In this regard, it was determined that the six-factor structure of the draft scale created after EFA was generally consistent and validated.

In the reliability analysis of the scale, internal consistency was evaluated. A Cronbach's alpha value between 0.70 and 1.00 is considered a criterion for the scale to be deemed reliable [45]. In the reliability analysis of the scale, the total Cronbach's alpha coefficient was found to be 0.885, and the Cronbach's alpha values for the subdimensions ranged from 0.610 to 0.883. The fact that the internal consistency coefficient of the Digital Detox Scale is above 0.70 supports the scale's reliability. Additionally, item-total correlations were examined for reliability, and it was determined that all items had a correlation above 0.30 [46]. This finding suggests that the items of the scale were correctly understood by the participants; consistent responses were given, and the items had high discriminative power [34, 46].

Limitation

This study's exclusive focus on university students in Türkiye restricts the generalizability of the findings to other cultural and demographic contexts. Future research should include participants from different countries and diverse educational settings to enable cross-cultural comparisons and assess the scale's broader validity. Additionally, the reliance on self-reported measures of digital device usage and digital detox habits may introduce social desirability bias, limiting the objectivity of the data. Incorporating objective digital tracking tools (e.g., screen time applications) in future studies would help overcome this limitation. Furthermore, the cross-sectional design of this study prevents causal inferences. Longitudinal and experimental designs are needed to better evaluate the long-term impacts of digital detox on psychological and behavioral outcomes. Lastly, the study did not explore moderating factors such as personality traits, socio-economic status, or academic workload, which could significantly shape digital detox behaviors and should be examined in future research.

Practical Implications

The developed DDS provides an important tool for evaluating individuals' ability to regulate their digital device usage and engage in digital detox processes. Beyond academic applications, the DDS can be employed to assess the effectiveness of intervention programs designed to promote healthier digital habits. Universities and schools can integrate the scale into digital literacy and well-being programs to encourage students to develop self-regulatory strategies for digital device management. Policymakers may also use the findings to design public health campaigns that raise awareness about the psychological and social consequences of excessive technology use. Additionally, mental health professionals and counselors can apply the DDS in clinical settings to identify individuals at risk of digital overuse and tailor support programs accordingly. Taken together, the DDS not only contributes to the academic literature but also offers actionable insights for educators, practitioners, and decision-makers seeking to foster more balanced and mindful technology use in the digital age.

Conclusion

This study aimed to develop a valid and reliable scale to assess university students' digital detox levels. The DDS is a psychometrically sufficient measurement tool, as shown by the thorough validity and reliability analyses. Covering components such as limiting digital device usage, regulating digital content consumption habits, and prioritizing social interactions, this scale stands out as a tool that can help individuals manage their interactions with the digital world more consciously. The findings provide an important foundation for future research evaluating the impact of digital detox on individual well-being.

Ethical Considerations

The study has been approved by the Scientific Research and Publication Ethics Committee of Artvin Coruh University (protocol no: E-18457941-050.99-175305). Participants were informed about the purpose of the research, and written Consent to Participate was obtained from each individual. Interviews were conducted in settings that ensured privacy, and each participant was assigned a unique code to anonymize their identity. The data were used solely for the purposes of this study, and no identifying information was included in any publications. All procedures were carried out in accordance with the ethical principles of the Declaration of Helsinki.

Author Contributions **Aslı Akdeniz Kudubeş**: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing–original draft, **Özkan Özbay**: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing–original draft, **Metin Beşaltı**: Conceptualization, Data curation, Investigation; Methodology, Project Validation, Visualization, Writing–original draft, **Sevil Çınar Özbay**: Conceptualization, Data curation, Investigation; Methodology, Project Visualization, Writing–original draft, **Selma Durmuş Sarıkahya**: Conceptualization, Data curation, Investigation; Methodology, Project Visualization, Writing–original draft.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethical Considerations The study has been approved by the Scientific Research and Publication Ethics Committee of Artvin Coruh University (protocol no: E-18457941-050.99-175305). Participants were informed about the purpose of the research, and written Consent to Participate was obtained from each individual. Interviews were conducted in settings that ensured privacy, and each participant was assigned a unique code to anonymize their identity. The data were used solely for the purposes of this study, and no identifying information was included in any publications. All procedures were carried out in accordance with the ethical principles of the Declaration of Helsinki.

Ethical Approval The study has been approved by the Scientific Research and Publication Ethics Committee of a university (approval number E-18457941-050.99-157105, Date: 21.11.2024).

Informed Consent All participants took part voluntarily and were informed about the objectives of the study.

Competing Interests The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Orlikowski WJ. Digital work: a research agenda. In: Czarniawska B, editor. A research agenda for management and organization studies. Cheltenham: Elgar; 2016. pp. 88–95. https://doi.org/10.4337/9781784717025.00014.
2. Vanden Abeele MMP, Mohr V. Media addictions as apparatgeist: what discourse on TV and smartphone addiction reveals about society. Convergence. 2021;27(6):1536–57. https://doi.org/10.3200/JOER.99.6.323-338.
3. Özbay Ö, Çınar Özbay S, Akdeniz Kudubeş A, Durmuş Sarıkahya S, Beşaltı M. Development and psychometric analysis of the digital obesity scale. ınt J human–computer Interact. 2025;1–10. https://doi.org/10.1080/10447318.2025.2504183.
4. Jiang Y, Balaji MS. Getting unwired: what drives travellers to take a digital detox holiday? Tour Recreat Res. 2022;47(5–6):453–69. https://doi.org/10.1080/02508281.2021.1889801.
5. Baym NK, Wagman KB, Persaud CJ. Mindfully scrolling: rethinking Facebook after time deactivated. Social Media + Society. 2020. https://doi.org/10.1177/2056305120919105.
6. Jorge A. Social media, interrupted: users recounting temporary disconnection on Instagram. Soc Media + Soc. 2019;5(4):2056305119881691. https://doi.org/10.1177/2056305119881691.
7. Mannell K. A typology of mobile messaging's disconnective affordances. Mob Media Commun. 2019;7(1):76–93. https://doi.org/10.1177/2050157918772864.
8. Nguyen MH. Managing social media use in an always-on society: exploring digital wellbeing strategies that people use to disconnect. Mass Commun Soc. 2021;24(6):795–817. https://doi.org/10.1080/15205436.2021.1979045.
9. Radtke T, Apel T, Schenkel K, Keller J, von Lindern E. Digital detox: an effective solution in the smartphone era? A systematic literature review. Mob Media Commun. 2022;10(2):190–215. https://doi.org/10.1177/20501579211028647.
10. Schmuck D. Does digital detox work? Exploring the role of digital detox applications for problematic smartphone use and well-being of young adults using multigroup analysis. Cyberpsychol Behav Soc Netw. 2020;23(8):526–32. https://doi.org/10.1089/cyber.2019.0578.
11. Brennen B. Opting out of digital media. Routledge; 2019.
12. Karppi T, Disconnect. Facebook's affective bonds. U of Minnesota; 2018.
13. Syvertsen T, Enli G. Digital detox: media resistance and the promise of authenticity. Convergence. 2020;26(5–6):1269–83. https://doi.org/10.1177/135485651984732.
14. Wilcockson TDW, Osborne AM, Ellis DA. Digital detox: the effect of smartphone abstinence on mood, anxiety, and craving. Addict Behav. 2019;99:106013. https://doi.org/10.1016/j.addbeh.2019.06.002.
15. Oxford Dictionaries. Definition of digital detox in english. How to break up with your phone. Ten Speed; 2019. http://www.oxforddictionaries.com/definition/english/digital-detoxPrice.
16. Choi SB, Lim MS. Effects of social and technology overload on psychological well-being in young South Korean adults: the mediatory role of social network service addiction. Comput Human Behav. 2016;61:245–54.
17. Choi S, Jeong H, Ko M, Lee U. LockDoll: providing ambient feedback of smartphone usage within social interaction. In: Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems. 2016. pp. 1165–1172. https://doi.org/10.1145/2851581.2892445
18. Ko M, Choi S, Yang S, Lee J, Lee U. FamiLync: facilitating participatory parental mediation of adolescents' smartphone use. In: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. 2015. pp. 167–878. https://doi.org/10.1145/2750858.2804283
19. Ko M, Yang S, Lee J, Heizmann C, Jeong J, Lee U et al. NUGU: a group-based intervention app for improving self-regulation of limiting smartphone use. In: Proceedings of the 18th ACM conference on computer supported cooperative work & social computing. 2015. pp. 235–1245. https://doi.org/10.1145/2675133.2675244
20. Albayrak ES. Sosyal Medya Platformlarında Dijital detoks: Deneysel Bir Araştırma. Selçuk Üniversitesi Sos Bilim Enstitüsü Derg. 2020;44:252–66.
21. Kushlev K, Dunn EW. Checking email less frequently reduces stress. Comput Hum Behav. 2015;43:220–8. https://doi.org/10.1016/j.chb.2014.11.005.
22. Zahariades D. Digital detox: the ultimate guide to beating technology addiction, cultivating mindfulness, and enjoying more creativity, inspiration, and balance in your life! Art of Productivity; 2018.
23. Syvertsen T, Enli G. Digital detox: media resistance and the promise of authenticity. Convergence: Int J Res into New Media Technol. 2019;26(5–6):1269–83. https://doi.org/10.1177/1354856519847325.
24. Brown L, Kuss DJ. Fear of missing out, mental wellbeing, and social connectedness: a seven-day social media abstinence trial. Int J Environ Res Public Health. 2020;17(12):4566. https://doi.org/10.3390/ijerph17124566.

25. Fu S, Li H, Liu Y, Pirkkalainen H, Salo M. Social media overload, exhaustion, and use discontinuance: examining the effects of information overload, system feature overload, and social overload. Inf Process Manag. 2020;57(6):102307. https://doi.org/10.1016/j.ipm.2020.102307.
26. Coyne P, Woodruff SJ. Taking a break: the effects of partaking in a two-week social media digital detox on problematic smartphone and social media use, and other health-related outcomes among young adults. Behav Sci. 2023;13(12):1004. https://doi.org/10.3390/bs13121004.
27. Hall JA, Xing C, Ross EM, Johnson RM. Experimentally manipulating social media abstinence: results of a four-week diary study. Media Psychol. 2021;24(2):259–75. https://doi.org/10.1080/15213269.2019.1688171.
28. Hanley SM, Watt SE, Coventry W. Taking a break: the effect of taking a vacation from Facebook and Instagram on subjective well-being. PLoS ONE. 2019;14(6):e0217743. https://doi.org/10.1371/journal.pone.0217743.
29. Vanman EJ, Baker R, Tobin SJ. The burden of online friends: the effects of giving up Facebook on stress and well-being. J Soc Psychol. 2018;158(4):496–508. https://doi.org/10.1080/00224545.2018.1453467.
30. Marx J, Mirbabaie M, Turel O. Digital detox: a theoretical framework and future research directions for information systems. Inf Manage. 2025;62(1):104068. https://doi.org/10.1016/j.im.2024.104068.
31. Forster M, Stangl FJ, Riedl R. Exploring themes in digital detox research: Insights from a literature review. 2024.
32. Hager N, Stangl FJ, Riedl R. Digital Detox Research: An Analysis of Applied Methods and Implications. In: Conceptualizing Digital Responsibility for the Information Age: Proceedings of the 18th International Conference on Wirtschaftsinformatik, Paderborn, Germany, 2023, Vol 1. Springer Nature; 2025. p. 359.
33. Creswell JW. Educational research: planning, conducting, and evaluating quantitative and qualitative research. pearson; 2015.
34. Buyukozturk S. Sosyal bilimler Için veri analizi El kitabı: istatistik, Araştırma Deseni SPSS Uygulamaları ve Yorum [Data analysis handbook for social sciences: Statistics, research design, SPSS applications and interpretation]. Ankara: Pegem Akad. 2017.
35. Şencan H. Reliability and validity in social and behavioral measurements. Ankara Seçkin Publ. 2005.
36. DeVellis RF, Thorpe CT. Scale development: theory and applications. Sage; 2021.
37. Çapık C, Gözüm S, Aksayan S. Kültürlerarası Ölçek Uyarlama aşamaları, Dil ve kültür Uyarlaması: güncellenmiş Rehber. Florence Nightingale J Nurs. 2018;26(3):199–210.
38. Davis LL. Instrument review: getting the most from a panel of experts. Appl Nurs Res. 1992;5(4):194–7.
39. Arifin WN. Exploratory factor analysis and cronbach's alpha. Dim. 2017;1(150):12.
40. Kline P. An easy guide to factor analysis. Routledge; 2014.
41. Clark DA, Bowles RP. Model fit and item factor analysis: overfactoring, underfactoring, and a program to guide interpretation. Multivar Behav Res. 2018;53(4):544–58. https://doi.org/10.1080/00273171.2018.1461058.
42. Schreiber JB, Nora A, Stage FK, Barlow EA, King J. Reporting structural equation modeling and confirmatory factor analysis results: A review. J Educ Res. 2006;99(6):323–38. https://doi.org/10.3200/JOER.99.6.323-338.
43. Capik JM, Molnar TJ. Flowering phenology of Eastern Filbert blight-resistant hazelnut accessions in new Jersey. HortTechnology. 2014;24(2):196–208.
44. Erkorkmaz Ü, Etikan İ, Demir O, Özdamar K, Sanisoğlu SY. Doğrulayıcı Faktör analizi ve Uyum indeksleri. Turkiye Klin J Med Sci. 2013;33(1):210–23.
45. Alpar R. Applied statistics and validity-reliability with examples from sports, health and educational sciences. Ankara: Detay Yayincilik; 2016.
46. Henson RK, Roberts JK. Use of exploratory factor analysis in published research: common errors and some comment on improved practice. Educ Psychol Meas. 2006;66(3):393–416. https://doi.org/10.1177/0013164405282485.

Authors and Affiliations

Aslı Akdeniz Kudubeş[1] · Özkan Özbay[2] · Metin Beşaltı[3] · Sevil Çınar Özbay[4] · Selma Durmuş Sarıkahya[5]

✉ Sevil Çınar Özbay
cinarsevil87@gmail.com

Aslı Akdeniz Kudubeş
aslikudubes@gmail.com

Özkan Özbay
ozkanozbay87@gmail.com

Metin Beşaltı
besalti@artvin.edu.tr

Selma Durmuş Sarıkahya
durmussel@gmail.com

1 Child and Disease Nursing Department, Faculty of Health Sciences, Bilecik Şeyh Edebali University, Bilecik, Türkiye

2 Distance Education Application and Research Center, Artvin Çoruh University, Artvin, Türkiye

3 Department of Educational Sciences, Artvin Çoruh University, Artvin, Türkiye

4 Faculty of Health Sciences, Artvin Çoruh University, Artvin, Türkiye

5 Department of Public Health Nursing, Faculty of Health Sciences, Artvin Çoruh University, Artvin, Türkiye