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The Boselt NoFix Notification-Checking Obsession Scale—Development of the Adolescent Form and Analysis of Its Psychometric Properties

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ABSTRACT

This study aimed to develop the *Boselt NoFix (Notification Fixation) Notification-Checking Obsession Scale–Adolescent Form* to assess excessive notification-checking behaviors and related obsessive–compulsive patterns among adolescents aged 12–18 years and to examine its psychometric properties. The study was conducted in three consecutive phases using three independent samples and included a total of 736 adolescents residing in Turkey (mean age = 15.20 years, SD = 1.10; 50.7% female). Exploratory factor analysis revealed an eight-item scale with a two-factor structure (obsession and compulsion), explaining 71.1% of the total variance. Confirmatory factor analysis indicated good model fit. The overall reliability of the scale was high (Cronbach's $\alpha = .90$; McDonald's $\omega = .91$), with subscale reliability coefficients ranging from .85 to .87. Test–retest analyses demonstrated temporal stability. The total score and sub-dimensions showed positive, moderate correlations with digital amnesia, supporting external validity. The NoFix Scale is a valid and reliable instrument for assessing notification-based digital control behaviors in adolescents.

KEYWORDS

Adolescents; smartphone notifications; psychometrics; validity; reliability

1. Introduction

In today's digital age, smartphones and social media applications have become integral to individuals' daily lives. Particularly among adolescents and young populations, the use of digital devices has evolved beyond a means of communication into a way of life (Durak & Seferoğlu, 2018). Adolescence is a critical developmental stage characterized by accelerated cognitive, emotional, and social changes; an increased need for social belonging and peer acceptance; and the formation of identity and behavioral patterns (Uktamovna, 2025). These developmental characteristics suggest that adolescents' engagement with digital environments extends beyond individual usage habits and is closely linked to the fulfillment of social needs. In this context, internet-based applications and social media platforms function not only as communication tools but also as important spaces where adolescents maintain social connections, reinforce their sense of belonging, and seek social approval (Fabris et al., 2024; Reid Chassiakos et al., 2016; Smith et al., 2021).

The literature on internet, digital device, and social media use among adolescents presents rich, multidimensional, and noteworthy findings across various thematic domains. Research conducted between 2000 and 2022 across 36 countries—including North America, Latin America, Europe, and Asia—indicates a significant increase in the duration of internet and electronic device use among adolescents (Twenge, 2026). Additionally, it has been reported that 21.8% of adolescents check their smartphones every five minutes, while 95% go to bed with their phones and check them immediately upon waking (Durak & Seferoğlu, 2018; Hoşgör, 2020). In another study, adolescents were found to check their smartphones more frequently than adults and to place greater importance on digital interactions (Montag et al., 2015; Montag & Diefenbach, 2018).

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Research examining the effects of digital device use on adolescents' daily functioning, academic performance, and cognitive processes indicates that excessive digital engagement may be associated with various negative outcomes. Previous studies have reported that nighttime social media use is related to poorer sleep quality (Lin et al., 2024), intensive electronic device use is associated with lower academic performance (Twenge, 2026), and digital media exposure may contribute to attentional difficulties and changes in executive functioning (Baumgartner et al., 2024; Clemente-Suárez et al., 2024). Furthermore, increasing dependence on digital technologies for accessing and storing information has been discussed within the framework of digital amnesia. Studies suggest that reliance on digital tools may influence memory processes and information retention (Cheremoshkina, 2011; Kaspersky Lab, 2015; Marsh & Rajaram, 2019; Robert et al., 2024; Sparrow et al., 2011). Overall, these findings highlight the importance of examining specific digital behavior patterns that may affect adolescents' cognitive and behavioral functioning.

Beyond these findings, the existing literature indicates that the use of digital devices and social media platforms among adolescents also has significant implications for social connectedness, sense of belonging, and behavioral regulation processes. Research in this area suggests that a sense of belonging to social media is negatively associated with psychological maladjustment and that social media use may serve as a tool for maintaining relationships established in school settings (Fabris et al., 2024). Additionally, digital environments have been shown to strengthen offline relationships and facilitate communication beyond geographical constraints (Marlowe et al., 2017). Furthermore, adolescents today tend to prefer visually oriented social media platforms over traditional text-based communication channels, as well as group-based interaction tools such as WhatsApp. It has been reported that exclusion from WhatsApp groups by peers is associated with emotional symptoms among adolescents (Marengo et al., 2021). In this context, a more comprehensive understanding of the effects of digital device use in adolescents requires examining the underlying processes and mechanisms that drive such behaviors.

Notifications generated by the internet, social media applications, and digital platforms can function as immediate social signals that inform adolescents about peer interactions, inclusion in social exchanges, and ongoing group dynamics (Nesi et al., 2018). Therefore, missing notifications may be perceived not merely as a technological absence but also as a potential threat to social connectedness and belongingness among adolescents (Beyens et al., 2016; Reid Chassiakos et al., 2016). In this context, the need to remain constantly connected through instant messaging and social media notifications may increase individuals' fear of missing out (FoMO), intensifying anxiety and cognitive preoccupation, and over time leading notification-checking behaviors to acquire an obsessive quality (Elhai et al., 2016; Yang et al., 2020). Consistent with this, research has shown that peer exclusion from WhatsApp groups is positively associated with FoMO among adolescents (Marengo et al., 2021).

Although FoMO provides an important conceptual framework for explaining individuals' tendency to remain continuously connected to digital environments, this process may not always be fully captured by the notion of being absent from digital platforms. Particularly in notification-based digital interactions, the experience of "missing out" may arise not from the absence of content itself, but from not receiving notifications or failing to notice them in a timely manner. This suggests that the fear of missing out is not solely related to access to digital environments, but is also closely associated with the continuity and accessibility of notifications. Therefore, the concept of FoMO may be limited in fully explaining this specific process, highlighting the need for new conceptual frameworks that more explicitly address obsessive thoughts and compulsive checking behaviors related to notifications. In this context, the concept of "Notification Fixation" (NoFix) may offer a meaningful approach for understanding individuals' thoughts about missing digital notifications and the accompanying control behaviors.

The term "NoFix (Notification Fixation)" refers to the propensity of individuals to constantly and frequently check their smartphones for notifications, particularly out of fear of missing calls, messages, or social media alerts. Similar to obsessive-compulsive thought patterns, NoFix is characterized by hypersensitivity, anxiety, distractibility, and compulsive checking behaviors in response to digital stimuli (APA, 2013; Kanbay, Akçam, et al., 2025). Particularly in adolescents, this behavior pattern has adverse effects on attention, sleep patterns, academic performance, and mental well-being (Montag et al., 2015;

Rosen & Samuel, 2015). NoFix is a condition where an individual gets an intense internal urge to check digital notifications and is unable to control this urge (Kanbay, Akçam, et al., 2025). This behavior manifests itself as the individual unconsciously checking their smartphone screen frequently, experiencing vibrations without notification sounds (Phantom Vibration Syndrome), or developing an involuntary reflex of unlocking the screen (Laramie, 2007; Rothberg et al., 2010).

Although NoFix shares certain characteristics with existing digital behavior constructs, it differs conceptually in terms of its primary psychological focus and underlying mechanism. Fear of Missing Out (FoMO) primarily explains individuals' concerns about missing rewarding social experiences and their motivation to remain socially connected (Przybylski & Weinstein 2013). Although FoMO has consistently been associated with problematic smartphone use, excessive social media engagement, and repetitive smartphone checking (Elhai et al., 2016; Yang et al., 2020), its central mechanism remains the anticipation of missing social experiences rather than digital notifications themselves. Similarly, nomophobia refers to the anxiety experienced when individuals are unable to access or use their mobile phones (King et al., 2013), whereas NoFix may occur even when the smartphone is fully accessible and instead reflects persistent concerns about missing incoming notifications (Kanbay, Öztürk, et al., 2025). Problematic smartphone use and smartphone addiction describe broader patterns of excessive smartphone engagement characterized by impaired self-regulation, loss of control, and functional impairment (Elhai et al., 2018; Xie et al., 2023). In contrast, NoFix focuses specifically on persistent cognitive preoccupation with digital notifications together with repetitive notification-checking behaviors driven by concerns about missing incoming notifications (Kanbay, Öztürk, et al., 2025).

Other constructs have also been proposed to explain behaviors associated with intensive smartphone use. For example, compulsive phone checking primarily emphasizes habitual and repetitive checking behaviors (Duke & Montag, 2017), whereas Phantom Vibration Syndrome refers to the false perception of phone vibrations or notifications in the absence of external stimuli (Laramie, 2007; Rothberg et al., 2010). Likewise, digital dementia has been used to describe cognitive decline associated with excessive dependence on digital technologies (Spitzer, 2012). Although these constructs contribute to understanding specific aspects of problematic digital technology use, none specifically conceptualizes persistent notification-related cognitive preoccupation together with compulsive notification-checking behaviors as a distinct psychological construct. Accordingly, NoFix should not be considered a replacement for FoMO, nomophobia, problematic smartphone use, smartphone addiction, or other related constructs; rather, it is proposed as a complementary notification-centered framework that explains a specific cognitive–behavioral process associated with digital notifications (Kanbay, Öztürk, et al., 2025).

The growing centrality of digital notifications in everyday communication highlights the need for measurement tools capable of assessing notification-specific cognitive and behavioral tendencies. Existing instruments primarily assess broader aspects of smartphone use, technology-related anxiety, or social concerns, whereas no instrument has specifically focused on persistent notification-related cognitive preoccupation and repetitive notification-checking behaviors. To further clarify the theoretical positioning of NoFix, Supplementary Table 1 presents a comprehensive comparison of its similarities and differences with FoMO, nomophobia, problematic smartphone use, smartphone addiction, compulsive phone checking, Phantom Vibration Syndrome, digital dementia, and related digital behavior constructs.

1.1. Aim of the study

In light of the existing evidence, adolescence is recognized as a critical developmental period characterized by significant cognitive, emotional, and social changes (Uktamovna, 2025). During this stage, the use of digital technologies carries the risk of evolving into problematic usage patterns, potentially leading to various issues related to cognitive processes, social belonging, and behavioral patterns. Therefore, addressing digital-related problems from a comprehensive perspective is essential for protecting adolescent health and minimizing the adverse effects of the digital age. Accordingly, the availability of a valid and reliable measurement tool to assess notification-based obsessive thoughts and compulsive behavioral tendencies in adolescents is of considerable importance. Although there are several psychometric instruments in the literature assessing internet-related addictive behaviors—such as internet addiction, problematic internet use, and digital gaming addiction—there is a notable lack of a measurement tool specifically designed to assess NoFix. Based on this gap in the literature, the present study aims to develop the Boselt NoFix Notification Fixation Scale–Adolescent Form and to examine its psychometric properties.

The scale developed within the scope of this study has the potential to be one of the first measurement tools that systematically evaluates obsessive thoughts and control behaviors related to digital notifications, thereby addressing an important gap in the literature. Furthermore, it is expected that this scale will contribute to a better understanding of risks emerging from digital environments and serve as a foundation for interventions aimed at protecting psychosocial health.

2. Material and method

2.1. Research objective and type

The primary objective of this study was to develop the Boselt NoFix NCOS-AF, a unique, psychometrically valid, and reliable measurement tool to assess obsessive thoughts and compulsive behavior toward digital notifications among teenagers. Since this study aimed to develop the measurement tool mentioned, it required factor analysis techniques and a specific methodology. Therefore, the study design was based on a methodological research type (DeVellis, 2014). Figure 1 summarizes the research methodology.

2.2. Research significance

Although the literature indicates that the NoFix concept is related to digital addiction, nomophobia, FOMO, and digital distraction, it offers a unique conceptual framework by focusing solely on notification-checking behaviors (Kanbay, Akçam, et al., 2025). This uniqueness fills a substantial research gap about analyzing sub-dimensions of digital behavior in more detail and developing intervention plans. Accordingly, it is possible to analyze the significance of this study through three main axes. First, the NoFix concept aims to provide a scientific basis for a digital behavior pattern frequently observed among teenagers but inadequately conceptualized, enabling the analysis of this behavior with a new measurement tool. Second, given that this behavior pattern potentially leads to adverse psychological consequences, including distraction, academic failure, sleep disorders, and anxiety, the scale can be

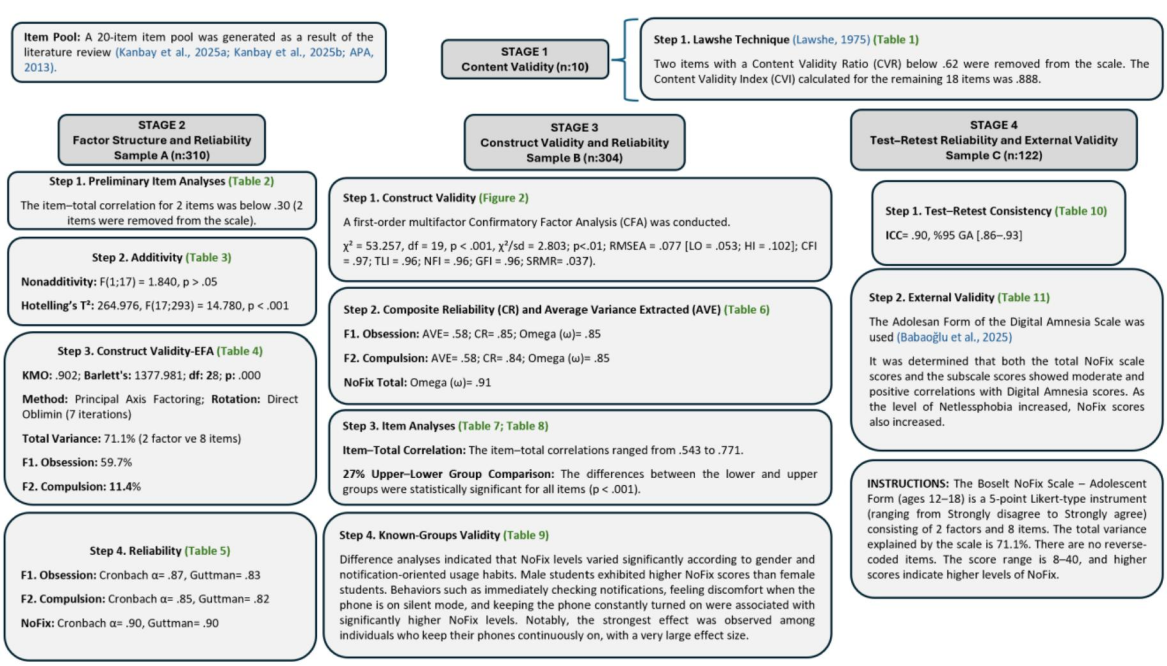

Figure 1. Summary of research methodology.

considered a significant tool for early diagnosis and prevention (Altmann et al., 2014; Rosen & Samuel, 2015). Thirdly, it is anticipated that the developed scale will be simple to use by researchers, educators, psychological counselors, and parents, thus contributing to better control of teenagers' digital behavior. As a result, this scale makes a significant theoretical and practical contribution to measuring digital notification-checking behaviors among teenagers and understanding the psychosocial effects of these behaviors. The developed scale will also provide a scientific basis for intervention studies on digital health, media literacy, and technology use among teenagers.

2.3. Item pool creation

The item pool for the Boselt NoFix NCOS-AF was developed through a literature review (APA, 2013; Kanbay, Akçam, et al., 2025; Kanbay, Öztürk, et al., 2025). Initially, a theoretical framework was established through reviewing scientific articles on digital addiction, notification management, attention splitting, impulsive technology use, and obsessive-compulsive behaviors. Subsequently, the study analyzed concepts such as automatic responses individuals develop toward notifications, the urge to repetitive notification-checking behaviors, fear of missing out (FOMO), and notification-related stress and anxiety levels. As a result, as designed to address notification-checking obsession in a multifaceted manner, the scale contained 20 items focusing on key components, such as cognitive processes (constantly thinking about notifications, attention splitting), behavioral responses (constantly checking notifications, urge to immediately respond to notifications), and emotional effects (feeling uneasy or anxious when not receiving notifications).

2.4. Pilot study

When developing and adapting measurement tools, the literature suggests conducting a pilot study using a group of 30–50 individuals with similar attributes to the target group (age, gender, education level, and similar attributes) (Boateng et al., 2018; Erkuş, 2012; Trochim & Donnelly, 2006). Accordingly, this study conducted a pilot study among 38 individuals and used the acquired data to analyze the items. As a result, the study determined that the items in the draft form were comprehensible.

2.5. Study population and sample

The study population consisted of teenagers aged 12–18 residing in various geographical regions across Turkey. Participants in the study sample were selected using a convenience sampling method with the following inclusion criteria: parental permission, owning a smartphone, volunteering to participate in the research, and responding to all questions on the form. This study required the use of factor analysis techniques, as it entailed scale development. According to the literature, factor analysis requires a sample of at least 300 individuals (Comrey & Lee, 2013). However, this study aimed to surpass the recommended sample size of 300 for both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The data collection phase involved three stages; accordingly, the study collected data from three different samples at consecutive times. Sample A consisted of 310 teenagers (used for preliminary item analyses, EFA, non-additivity analysis, and Hotelling's T2 test, in addition to calculating Cronbach's α reliability coefficient, Guttman coefficient, and Spearman-Brown split-half consistency). Similarly, Sample B contained 304 teenagers (used for CFA, AVE (Average Variance Extracted), CR (Composite Reliability), McDonald's Omega (ω), and Fornell–Larcker values were used for 27% upper-lower group comparison, post-item analyses, and Known-Groups Validity analyses). However, Sample C included 122 teenagers (used for test-retest consistency and external validity). As a result, the study sample consisted of a total of 736 individuals.

2.5.1. Sample features

Considering Sample A, 54.5% of participants were girls, and 34.2% were 9th-grade primary school students. Approximately 43.2% of participants checked their smartphones as soon as they heard notification sounds. However, when their phones were off, 15.8% always felt uneasy, and 13.5% occasionally. The mean age for sample A was 15.4 ± 1.1, and the average daily phone usage time was 4.7 ± 2.8 hr. Regarding sample B, 52.6% of participants were girls, and 33.2% were 9th-grade primary school students. Nearly 40.8% of participants checked their smartphones immediately after receiving notifications upon hearing notification sounds, while 16.1% always and 12.5% sometimes experienced unease when their phones were off. The mean age for sample B was 15.3 ± 1.2, and the average daily phone usage time was 4.4 ± 2.7 hr. Concerning sample C, 45.1% were girls, and 42.6% were 9th-grade primary school students. 37.7% of them immediately check their phones when they hear notification sounds, and 13.9% experience unease when their phones are off, with 13.9% experiencing it sometimes. The average age for sample C was calculated as 14.9 ± 1.0, and the average daily phone usage time was 4.1 ± 2.4 hr. Samples A, B, and C and the pilot sample ($n = 38$) were drawn from the same target population using identical inclusion criteria. Therefore, the four samples were considered comparable with respect to their general participant characteristics.

2.6. Data collection and inclusion criteria

The data collection process involved a mixed approach, using both online and face-to-face interview methods. Accordingly, researchers followed two different approaches to reach participants. First, participation in the research was voluntary and was facilitated through the Google Forms application. The scale form has been shared online along with a statement explaining research objectives, confidentiality principles, and ethical consent. Following the approval of the written informed consent form, participants responded to the questions with parental permission, and researchers recorded the data digitally. Only one submission was accepted per device to avoid duplicate entries. Researchers did not collect any personal information or record any IP addresses. Accordingly, the data was evaluated in an entirely anonymous manner. Second, researchers used the same scale form in face-to-face interviews for participants with limited or no online access. In this process, researchers applied the snowball sampling method to contact parents of children aged 12–18, and, after receiving their permission, they distributed printed data collection forms to the children. Thus, this process aimed to obtain balanced data from participants displaying varying access levels.

The inclusion criteria for the face-to-face sample were: (a) being between 12 and 18 years of age, (b) providing written parental consent, (c) voluntarily agreeing to participate in the study, and (d) completing all study questionnaires without missing data. For the online sample, participants were required to (a) be between 12 and 18 years of age, (b) have parental consent obtained through the online consent procedure, (c) voluntarily participate in the study, and (d) complete all questionnaires in full.

2.7. Data analysis

The study performed SPSS v.26 (Statistical Package for the Social Sciences) and AMOS 23.0 (Analysis of Moment Structures) software packages in data analysis. Numbers, means, and percentages presented descriptive statistics. Correlation analysis and the t-test were used to identify the relationship and variable differences, respectively. Within the scope of the normality assumption, the skewness and kurtosis values for each item revealed that the assumptions of normal distribution were met (George & Mallery, 2010). Since all variables were measured using self-report instruments at a single time point, common method variance was assessed using Harman's single-factor test. The results showed that the first unrotated factor explained 37.3% of the total variance, which was below the recommended threshold of 50%, indicating that common method variance was unlikely to substantially affect the findings of the present study.

While Lawshe's technique tested the content validity of the scale, EFA and CFA assessed its construct validity. For CFA, the fit indices used were χ^2/df (Chi-Square/Degrees of Freedom), RMSEA (Root Mean Square Error of Approximation), CFI (Comparative Fit Indices), TLI (Tucker–Lewis Index), GFI (the Goodness-of-Fit Index), NFI (Normed Fit Index), and SRMR (Standardized Root Mean Square Residual) (Hu & Bentler, 1999). Furthermore, the study utilized Cronbach's alpha coefficient and McDonald's Omega (ω) values to analyze the reliability of the scale and assess item-total correlations. AVE and CR values were interpreted to assess convergent and divergent validity (Fornell & Larcker, 1981). Finally, the study conducted a test-retest to evaluate the measurement consistency of the construct over time and identified correlations with the Digital Amnesia Scale Adolescent Form (Babaoğlu et al., 2025) to test external validity. The significance level was $p < 0.05$ for all statistical analyses.

2.8. Ethical values

This study received the required approvals from the Scientific Research and Publication Ethics Board of Artvin Çoruh University (Date: 19.09.2025, Decision No: E-18457941-050.99-193830). The study adhered to the ethical principles in the Declaration of Helsinki (World Medical Association, 2013). In accordance with privacy principles, participants' personal data was kept confidential and used solely for scientific purposes. Researchers also informed participants of their right to withdraw from the study at any time without reason. The study utilized an artificial intelligence-based generative tool (ChatGPT, OpenAI) only to support language and grammar editing. The authors designed the research, collected and analyzed the study data, and generated all the scientific content; as a result, they take full responsibility. No generative AI tool is listed as an author.

3. Results

This section presents the validity and reliability findings of the scale, the verification of the resultant construct, and related discussions, explaining the findings under various stages and steps.

Stage 1. Content Validity: The content validity assessment of the scale was conducted using the Lawshe technique, based on opinions from 10 experts in the fields of psychology, child and adolescent psychiatry, psychiatric nursing, and measurement and evaluation. Accordingly, when the number of experts is '$n = 10$', the critical CVR value is taken as 0.62 to deem the relevant item sufficient in terms of scope (Lawshe, 1975).

According to the analysis results, the CVR values of the vast majority of scale items ranged between 0.80 and 1.00, which was above the critical threshold. Accordingly, these data indicate that the items represent the construct intended to be measured and are deemed suitable by experts. However, the CVR for items i6 and i12 was below the critical threshold (0.62); therefore, they were removed from the scale because they failed to meet the content validity. The Content Validity Index (CVI), calculated based on items that ensure content validity, was found to be 0.888 (Table 1). As a result, the final CVI value indicates that the overall content validity of the scale is at a high level and that the items properly represent the construct intended to be measured (Büyüköztürk, 2010; Lawshe, 1975; Polit & Beck, 2006).

Stage 2. Factor Structure and Reliability Analyses: To determine the scale's structure, item-total correlations were analyzed, additivity analysis was performed, factor structure was identified using EFA, and reliability analyses of the structure were conducted. Sample A ($n = 310$) was used for the analyses at this stage.

Step 1. Preliminary Item Analysis: The literature recommends analyzing item-total correlations before EFA (Exploratory Factor Analysis). Indeed, item-total correlations are a widely used method to improve the scale's validity and reliability. The item-total correlation should typically be 0.30 or higher. This value indicates that the item properly represents the overall structure of the scale (Nunnally & Bernstein, 1994). Low item-total correlations may indicate that the item poorly contributes to the structure and may lower the scale's reliability (DeVellis, 2014). If the item-total correlation coefficient is below 0.30, there may be a considerable problem with the item; as a result, either the item should be revised or excluded from the scale (Çokluk et al., 2014; Şencan, 2005).

Table 1. Content validity results.

No	Nu	N	CVR	Critical value	No	Nu	N	CVR	Critical value
i1	10	10	1.00	0.62	**i11**	10	10	1.00	0.62
i2	9	10	0.80	0.62	***i12**	7	10	0.40	0.62
i3	10	10	1.00	0.62	**i13**	9	10	0.80	0.62
i4	9	10	0.80	0.62	**i14**	10	10	1.00	0.62
i5	10	10	1.00	0.62	**i15**	9	10	0.80	0.62
***i6**	8	10	0.60	0.62	**i16**	10	10	1.00	0.62
i7	9	10	0.80	0.62	**i17**	9	10	0.80	0.62
i8	10	10	1.00	0.62	**i18**	10	10	1.00	0.62
i9	9	10	0.80	0.62	**i19**	9	10	0.80	0.62
i10	9	10	0.80	0.62	**i20**	9	10	0.80	0.62
Number of Expert = 10			**Critical Value** = 0.62					**KGİ [CVI]** = 0.888	

*Items deemed "Not Suitable" or "Need Revision" by experts and thus did not meet the content validity criteria and excluded from the study; Nu: Number of experts who provided an opinion of "Need Revision" for the item; N: Number of experts who provided an opinion for the item; CVR (Nu-N/2)/(N/2); Content Validity Ratio; CVI: Content Validity Index.

Table 2. Item-total correlations.

No	ITC	No	ITC	No	ITC	No	ITC
i1	0.656	**i7**	0.733	**i13**	0.532	**i18**	0.626
i2	0.634	**i8**	0.711	**i14**	0.713	**i19**	0.668
i3	0.724	**i9**	0.591	**i15**	0.787	***i20**	0.280
i4	0.764	**i10**	0.732	**i16**	0.724	–	–
i5	0.721	***i11**	0.236	**i17**	0.756	–	–

Sample A ($n = 310$) was used for the analyses; **ITC:** Item-total correlation; *Items with item-total correlation < 0.30 were excluded from the scale.

Table 3. ANOVA with Tukey's test for non-additivity and hotelling's T-Squared test.

Non-additivity	Sum of squares	df	Mean squares	*F*	*p*
Intergroup	4576.304	309	14.810	–	–
Intragroup	369.826	17	21.754	28.415	<0.001
Non-additivity	1.408	1	1.408[a]	1.840	0.175
Hotelling's T2	*F*	df1	df2	*p*	
264.976	14.780	17	293	<0.001	

Sample A ($n = 310$) was used for the analyses; **a:** Tukey's estimate of power to which observations must be raised to achieve additivity = 0.915; Grand Mean = 1.2505.

According to the analysis of the item-total correlations, the item-total correlation values of i11 and i20 were below 0.30, and they were excluded from the scale. Hence, 16 items remained in the item pool. As a result, the item-total correlations of the remaining items ranged from 0.532 to 0.787 (Table 2).

Step 2. Additivity: The study performed a non-additivity test to identify whether the draft scale has additive properties (Table 3).

According to Tukey's non-additivity test results (Table 3), the non-additivity effect size was statistically insignificant ($F = 1.840$, $p = 0.175$). This data indicates that the relationship between the scale items and individual scores displays an additive structure, and the total scores taken from the scale are statistically significant and usable. Additionally, the fact that the conversion coefficient recommended by Tukey's test for additiveness is 0.915 indicates that the data is naturally quite close to an additive structure and requires no conversion (Field, 2018, 2024; Kline, 2023; Tabachnick & Fidell, 2019; Tukey, 1994). Hotelling's T-squared test, used to evaluate whether the mean scores of the scale items were equal, also revealed statistically significant results (Hotelling's $T^2 = 264.98$, $F(17, 293) = 14.78$, $p < 0.001$). This data also demonstrates that participants' responses to the items differed significantly, and the scale has a discriminative and variance-generating measurement structure (Hair et al., 2019).

Step 3. Construct Validity: This test reveals the extent to which the measurement tool accurately measures a theoretical construct (Strauss & Smith, 2009). EFA was conducted to identify how many

Table 4. EFA results for the scale's factor structure.

No	Item	Factor load	Variance
	F1. Obsession		
i3	I feel like I am missing notifications when I fail to check my smartphone.	0.914	59.7
i1	The feeling that I would miss notifications makes me anxious.	0.903	
i4	I feel uneasy when I fail to check notifications.	0.768	
i5	I feel the urge to check the screen even if I hear no notification sound.	0.638	
	F2. Compulsion		
i15	I always keep my phone with me so I do not miss any notifications.	0.944	11.4
i17	I keep my phone on at all times, as I am afraid of missing notifications.	0.781	
i18	I cannot sleep without checking my notifications.	0.726	
i19	I check my notifications repeatedly, even if I have already read them.	0.612	
	Total Variance: 71.1		
	KMO: 0.902; **Barlett's:** 1377.981; **df:** 28; *p*: <0.001		
	Method: Principal Axis Factoring; **Rotation:** Direct Oblimin (7 iterations)		

Sample A ($n = 310$) was used for analyses.

factors the items included in the scale could be grouped under (Costello & Osborne, 2005). Determining whether the data metric is appropriate for factor analysis is a prerequisite for EFA analysis. Additionally, the Kaiser-Meyer-Olkin (KMO) value and Bartlett's sphericity tests are the prerequisites. A KMO test result of ≥ 0.70 and a Bartlett's Sphericity Test score of $p < 0.05$ are considered statistically significant (Alpar, 2016).

Before EFA, the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity test results were used to assess the appropriateness of the data for factor analysis (Table 4). Accordingly, the KMO sample adequacy coefficient was 0.902, indicating that the sample is ideally suitable for factor analysis. Additionally, the Bartlett Sphericity test result was statistically significant [$\chi^2(28)=1377.981$, $p < 0.001$]. These values indicate that the items are correlated at a suitable level for factor analysis (Büyüköztürk, 2010).

For EFA, the "direct oblimin technique," a type of "oblique rotation" technique based on the assumption that factors are related to each other, was used as the factor rotation technique. Studies in the literature report various criteria to evaluate factor loadings. While Hair et al. (2019) reported loading values of 0.40 and higher as permissible, this study adopted a stricter criterion and included items with factor loadings of 0.50 and above in the scale. In addition to factor loading criteria, items were evaluated based on cross-loading patterns and conceptual clarity. Items were removed if they had insufficient factor loadings (<0.50), showed substantial cross-loadings between factors, or reduced the theoretical interpretability of the factor structure. Overall, the item reduction process resulted in the sequential removal of 12 items across the content validity, preliminary item analysis, and EFA stages, yielding the final eight-item scale. This approach aimed to retain strong factor-item relationships and achieve a more parsimonious and theoretically meaningful measurement model. As a result, the analyses supported a two-factor structure consisting of 8 items with eigenvalues greater than 1 (Table 4). The total variance explained by the scale was calculated as 71.1%.

Considering the theoretical structure of the NoFix concept, the first sub-dimension was named "Obsession," which consisted of four items (i1, i3, i4, i5). The factor loadings of these items ranged from 0.638 to 0.914, indicating that they strongly represent intense mental preoccupation and thoughts surrounding the notifications. The obsession factor explained 59.7% of the total variance. Similarly, considering the theoretical structure of the NoFix concept, the second sub-dimension was named "Compulsion," which contained four items (i15, i17, i18, i19). The factor loadings of these items also varied between 0.612 and 0.944, reflecting recurring and controlling behavioral patterns displayed to avoid missing notifications. The compulsion factor, however, explained 11.4% of the total variance. Considering the two factors together, they explained 71.1% of the total variance, a high rate for social science-developed scales, indicating a strong level of explanatory power. The high loading values of the items under the relevant factors and the absence of cross-loading issues reveal that the scale has an explicit, consistent, and theoretically meaningful factor structure.

Table 5. Reliability results.

Factor	Cronbach α	Split-half	Guttman
F1. Obsession	0.865	0.875	0.834
F2. Compulsion	0.848	0.817	0.817
NoFix	0.902	0.820	0.904

Sample A (*n* = 310) was used for analyses.

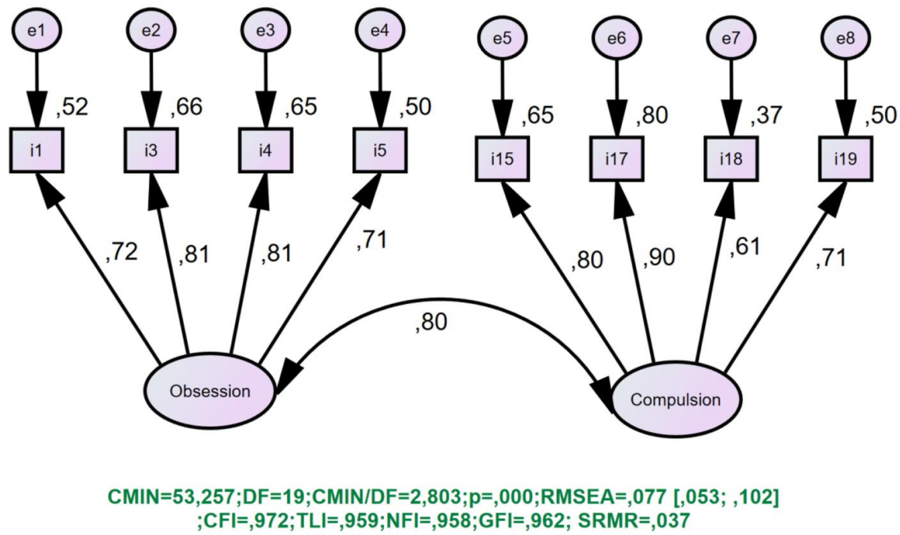

Figure 2. CFA results for the scale's factor structure.

Step 4. Reliability: This study calculated the Cronbach α reliability coefficient, Guttman coefficient, and Spearman-Brown split-half consistency to test construct reliability (Table 5). A reliability coefficient above 0.70 is recommended for a Likert-type scale; however, it should ideally be close to 1. Regarding the split-half consistency, the correlation between the two halves should be as high and significant as possible (DeVellis, 2014, p. 109; Şencan, 2005; Tezbaşaran, 2008).

According to the data in Table 5, the Cronbach's alpha, split-half, and Guttman coefficients for the obsession sub-dimension were 0.865, 0.875, and 0.834, respectively, indicating the sub-dimension's high level of internal consistency and the items' consistent measurement of the same construct. Similarly, for the compulsion sub-dimension, while the Cronbach's alpha coefficient was 0.848, the split-half and Guttman coefficients were both 0.817. These values also reveal that the compulsion sub-dimension has a reliable and consistent measurement structure. When all the scale items were considered together, the calculated Cronbach's alpha, split-half, and Guttman coefficients were 0.902, 0.820, and 0.904, respectively. These values indicate that the overall scale has a very high level of reliability and can be used confidently for research purposes (DeVellis, 2014; Field, 2018, 2024; Hair et al., 2019; Kline, 2023).

Stage 3. Construct Validity and Reliability Analyses: This stage involved validating the scales' factor structure, as well as reliability and item analyses (item-total correlations; 27% upper-lower group comparison). Additionally, changes in mean scale scores based on demographic variables were analyzed at this stage. Sample B (n = 304) was used for analyses.

Step 1. Construct Validity: The study performed the CFA to validate the scale's structure (Figure 2). This assessment is used to test the accuracy of the previously determined factor structure (Kline, 2023). While assessing the CFA results, the study also utilized common goodness-of-fit indices, including χ^2/df (Chi-Square/Degrees of Freedom); RMSEA (Root Mean Square Error of Approximation); CFI (Comparative Fit Indices); TLI (Tucker–Lewis Index); GFI (Goodness-of-Fit Index); NFI (Normed Fit Index); and SRMR (Standardized Root Mean Square Residual), while assessing the CFA results (George & Mallery, 2010; Kalaycı, 2014).

Table 6. AVE, CR, omega (ω) and Fornell–Larcker values.

Factor	n	AVE	CR	Omega (ω)
F1. Obsession	4	0.58	0.85	0.85
F2. Compulsion	4	0.58	0.84	0.85
NoFix	8	–	–	0.91
		Fornell-Larcker		
	F1	F2		
F1. Obsession	**(0.762)**			
F2. Compulsion	0.689**	**(0.762)**		

CR: Composite Reliability; **ω:** McDonald's Omega; **AVE:** Average Variance Extracted; Sample B ($n = 304$) was used for analyses.

The CFA results revealed that the two-factor first-level structure of the NoFix displayed 'good fit' (Figure 2). During the confirmatory factor analysis, modification indices were analyzed; however, it was deemed unnecessary to combine error terms. The analysis results also showed that the model's fit indices were within the permissible and good fit range (CMIN= 53.257; df= 19; CMIN/df= 2.803; $p < 0.001$; RMSEA= 0.077 [LO = 0.053; HI= 0.102]; CFI= 0.97; TLI= 0.96; NFI= 0.96; GFI= 0.96; SRMR= 0.037). These values indicate that the two-factor model is well-suited to the data and that structural validity is established (Hu & Bentler, 1999; Kline, 2023; Meydan & Şeşen, 2011; Schermelleh-Engel & Moosbrugger, 2003; Wang & Wang, 2012). The fact that all factor loadings are above 0.50 means that the items satisfactorily represent the relevant factors (Hair et al., 2019). The study also found that inter-factor correlations were significant, indicating that the dimensions are interrelated and discernible (Brown, 2015).

Step 2. Composite Reliability and Average Variance Extracted: Following CFA, convergent and discriminant validity were analyzed to assess the scales' construct validity (Table 6). AVE and CR values were calculated for each factor, and Fornell–Larcker analysis was performed using inter-factor correlations and AVE square roots. For the scale to have an AVE and CR, they must be 0.50 or higher and 0.70 or higher, respectively (Bagozzi & Yi, 1988; Hair et al., 2019).

The study found the AVE, CR, and Omega coefficients for the Obsession sub-dimensions as 0.58, 0.85, and 0.85, respectively. These values indicate that the sub-dimension displays a high degree of composite reliability and that the items accurately reflect the construct being measured. Similarly, for the Compulsion sub-dimension, the AVE, CR, and Omega coefficients were 0.58, 0.84, and 0.85, respectively. These results also reveal that the Compulsion sub-dimension presents a reliable and convergently valid measurement structure. Considering all scale items together, the McDonald's Omega coefficient was calculated as 0.91, indicating that the whole scale displays a high degree of reliability and that total score-based statistical analysis is viable (Kline, 2023; McDonald, 1999; Trizano-Hermosilla & Alvarado, 2016). Discriminant validity was assessed using the Fornell–Larcker criterion. Accordingly, the square root of the AVE values for each factor was observably higher than the inter-factor correlation coefficient. The study calculated the AVE square root for both obsession and compulsion factors as 0.762. However, the correlation level between the factors remained at 0.689 ($p < 0.01$), indicating that while both factors are related, the constructs are theoretically differentiated (Fornell & Larcker, 1981).

Step 3. Item Analyses: This step involves item correlations as part of the item analyses, and the findings were supported by upper-lower group analyses.

3.1. Item-total correlations

On the CFA-verified structure, item analyses were carried out. Item means, item-total correlations, and Cronbach's Alpha values (when an item was excluded) were analyzed to identify each item's contribution to the scale and its discriminative potential (Table 7).

Items' mean scores ranged from 1.04 to 1.57, whereas their standard deviations were between 1.15 and 1.29. These values reveal that the variances in response distributions of the items are satisfactory and display no significant upper-lower effect. Analysis of the item-total correlations (ITC) showed that

Table 7. Item means and item total correlations.

No	x	sd	α	ITC	No	x	sd	α	ITC
i1	1.14	1.16	0.883	0.625	**i15**	1.17	1.19	0.876	0.705
i3	1.11	1.21	0.878	0.685	**i17**	1.04	1.22	0.869	0.771
i4	1.17	1.15	0.875	0.720	**i18**	1.37	1.29	0.892	0.543
i5	1.57	1.24	0.880	0.662	**i19**	1.19	1.27	0.880	0.661

X: mean; **SD:** Standard deviation; α: Cronbach's Alpha when the item is deleted; **ITC:** Item-total correlation; Sample B ($n = 304$) was used for analyses.

Table 8. 27% Upper-lower group comparison (n = 82).

Item	Group	X	sd	*t*	*p*
F1. Obsession	**Upper**	10.3	2.34	34.930	<0.001
	Lower	0.7	0.82		
F2. Compulsion	**Upper**	10.2	2.7	31.766	<0.001
	Lower	0.3	0.61		
NoFix	**Upper**	19.6	4.99	31.221	<0.001
	Lower	1.7	1.45		

X: mean; **sd:** Standard deviation; ***t:*** independent samples t-test; ***p:*** significance value; Sample B ($n = 304$) was used for analyses.

all item values ranged from 0.54 to 0.77, well above the permissible threshold of 0.30, demonstrating that the items are highly consistent with the construct measured by the scale and are discriminative (Field, 2018, 2024; Nunnally & Bernstein, 1994). Additionally, in cases of deleting any item, the Cronbach's Alpha values do not significantly impact the overall reliability level of the scale, indicating that all items substantially contribute to the scale and that none should be deleted (Table 7).

3.2. Item discrimination analysis

This analysis involved the mean item scores comparisons of participants in the top 27% and bottom 27% of the total scores to identify the discriminative power of the scale's items. Accordingly, independent samples t-tests were used in the analyses (Table 8).

The study analyzed the scores between the upper and lower 27% groups on the NoFix and its sub-dimensions using independent samples t-tests on the lower and upper ($n = 82$ for both) groups selected from Sample B (Table 8). Accordingly, in both the Obsession and Compulsion sub-dimensions, the mean scores of the upper group were significantly higher than the lower group ($t = 31.766$–39.930, $p < 0.001$). Correspondingly, the mean score of the upper group was substantially higher than the lower group in terms of total scale score ($t = 31.221$, $p < 0.001$). These results indicate that the Boselt NoFix has high discriminatory power at both the sub-dimension and total score levels.

Step 4. Known-Groups Validity: This process involved identifying whether NoFix scores differed by demographic variables. Prior to gender-based comparisons, measurement invariance across gender was examined using multi-group confirmatory factor analysis. The results supported configural, metric, and scalar invariance, indicating that NoFix scores were comparable across female and male adolescents. Specifically, configural invariance indicated that the NoFix exhibited the same factor structure across gender, metric invariance demonstrated that the relationships between the latent construct and its indicators were equivalent, and scalar invariance supported meaningful comparisons of observed scores and latent means between female and male adolescents (Supplementary Table 2). In addition, floor and ceiling effects were examined to evaluate the score distribution of the scale. As presented in Supplementary Table 3, the proportions of participants obtaining the minimum and maximum possible scores were below the commonly accepted 15% threshold for both subscales and the total scale, indicating the absence of significant floor and ceiling effects (Terwee et al., 2007). Accordingly, intergroup differences were analyzed, and the degree of differences was determined using Cohen's d and η^2 effect sizes (Table 9).

Analysis revealed that the NoFix differed significantly depending on some demographic variables (Table 9). In the gender-based analysis, male students had significantly higher total scale scores than

Table 9. Known-groups validity.

Variables	Category	n	x	sd	Statistics	Effect
Gender	Female	160	6.3	3.6	t:−9.999	$d \approx 1.15$
	Male	144	13.6	8.5	p: <0.001	
Checking the smartphone immediately after receiving a notification	[a] Yes	124	13.1	8.1	F:27.074	$\eta^2 \approx 0.15$
	[b] No	75	6.4	5.9	p: <0.001	
	[b] Occasionally	105	8.2	5.5		
A feeling of unease when putting the phone on silent	[a] Yes	49	12.5	7.7	F:12.565	$\eta^2 \approx 0.08$
	[b] No	217	8.5	6.8	p: <0.001	
	[a] Occasionally	38	13.6	7.8		
Keeping the phone always on	[a] Yes	38	18.2	8.4	F:61.534	$\eta^2 \approx 0.29$
	[c] No	199	7.1	5.7	p: <0.001	
	[b] Occasionally	67	12.9	6.1		

a > b > c; Sample B ($n = 304$) was used for analyses; Post Hoc Multiple Comparisons: Tukey HSD.

Table 10. Test-retest reliability results.

Factor	ICC (2,1)	95% CI	p	Pearson r	Stability
F1. Obsession	0.87	[0.82-0.91]	<0.001	0.86	High
F2. Compulsion	0.85	[0.80-0.89]	<0.001	0.84	High
NoFix	0.90	[0.86-0.93]	<0.001	0.88	Excellent

Sample C (n = 122) was used for analyses. Intraclass correlation coefficients (ICC) were computed using the Two-Way Random-Effects Model (Absolute Agreement) approach. Interpretation criteria follow Koo and Li (2016): ICC < 0.50 = poor, 0.50–0.75 = moderate, 0.75–0.90 = good, and > 0.90 = excellent reliability.

female students [$t(302) = -9.999$, $p < 0.001$]. The calculated Cohen's d, $\approx$ 1.15, indicates a fairly large effect size for the difference (Cohen, 1988). Regarding 'checking the phone immediately upon receiving a notification,' ANOVA results revealed significant intergroup differences [$F(301)$=27.074, $p < 0.001$; η $\approx$ 0.15]. Similarly, there were substantial differences in the variable of 'feeling uneasy when putting the phone on silent' [$F(301)$=12.565, $p < 0.001$; $\eta^2 \approx 0.08$). However, the variable of tendency to 'keep the phone always on' resulted in the most significant difference [$F(301)$=61.534, $p < 0.001$). The calculated $\eta^2 \approx 0.29$ for this variable explicitly indicates a "larger effect size." Overall, individuals who displayed intense and consistent behavior toward notifications had significantly and strongly higher NoFix levels.

Stage 4. Test-Retest Reliability and External Validity: This stage involved examining the time measurement invariance and external validity of the output construct of the analyses. Accordingly, Sample C (n = 122) was used for these analyses.

Step 1. Test-Retest Reliability: This analysis was performed to assess the stability of the NoFix over time (Table 10). The scale was reapplied to the same group of participants two weeks after the first application, and, with the acquired data, the Intraclass Correlation Coefficient [ICC (2,1)] was calculated based on the Two-Way Random Effects Model (Absolute Agreement) (Koo & Li, 2016; Shrout & Fleiss, 1979). Pearson product-moment correlation coefficients were also evaluated (Field, 2018; Streiner et al., 2015).

Analyses revealed very high test-retest reliability for the NoFix at both the sub-dimension and total score levels (Table 10). Accordingly, the study determined the ICC values for the sub-dimensions of obsession and compulsion as 0.87 and 0.85, respectively, which indicate a good level of temporal reliability. Additionally, the ICC value for the total scale score was 0.90. This data also proved that the scale provided remarkably stable measurements over time (Koo & Li, 2016). The scale also produced reliable findings in repeated measurements, as supported by the strong Pearson correlation values (0.84–0.88).

Step 2. External Validity (Criterion/Convergent Validity): Criterion-related validity enables us to assess a measurement instrument by analyzing its relationship with another valid and reliable measurement tool known to measure similar or related constructs (Seçer, 2015). In this context, the correlations *(r)* of the NoFix with the Digital Amnesia Scale Adolescent Form (Babaoğlu et al., 2025) were examined to determine the external validity of the Boselt NoFix.

Table 11. NoFix and digital amnesia relationship.

	1	2	3	4
1. Obsession	**1**			
2. Compulsion	0.689**	**1**		
3. NoFix	0.816**	0.822**	**1**	
4. Digital Amnesia	0.352**	0.353**	0.384**	**1**

**Correlation is significant at the.
**0.01 significance level (2-tailed); Sample C ($n = 122$) was used for analyses.

The findings revealed positive and moderately significant relationships between digital amnesia and the sub-dimensions of obsession ($r = 0.352$, $p < 0.01$) and compulsion ($r = 0.353$, $p < 0.01$). Similarly, there was a positive and moderate correlation between the total NoFix score and digital amnesia ($r = 0.384$, $p < 0.01$). These findings explicitly indicate that NoFix and Digital Amnesia are related constructs representing different dimensions; as a result, it provides significant evidence supporting the criterion-related (external) validity of the scale (Table 11).

4. Discussion

The psychometric results of the Boselt NoFix, developed in this study, reveal that obsessive cognitive processes and accompanying notification-checking-related behavioral patterns are a consistent and quantifiable structure in adolescence. The two-factor structure (obsession and compulsion) obtained and validated by EFA and CFA demonstrates a high degree of alignment with the theoretical foundations of the NoFix concept. It also reveals that mental preoccupation with notification and behavioral responses aimed at regulating this preoccupation are discernible dimensions among adolescents (Kanbay, Akçam, et al., 2025).

Although the two dimensions of the NoFix are labeled as “Obsession” and “Compulsion,” these terms are not intended to represent clinical symptoms or diagnostic criteria associated with obsessive–compulsive disorder (OCD). Rather, they are used conceptually to characterize the cognitive and behavioral features of notification-related digital behavior. Specifically, “Obsession” refers to persistent cognitive preoccupation with smartphone notifications, whereas “Compulsion” reflects repetitive and difficult-to-resist notification-checking tendencies that emerge in response to this cognitive preoccupation. These labels were selected to describe the phenomenological characteristics of notification-focused behavior rather than to imply psychopathology. Accordingly, the NoFix is not a diagnostic instrument, and its scores should not be interpreted as indicators of OCD or any other psychiatric disorder. Instead, the scale is intended to assess notification-related cognitive and behavioral tendencies in non-clinical adolescent populations.

The two-factor structure of the adolescent form differs from the three-factor structure (cognitive obsession, behavioral control, and emotional regulation dimensions) reported in the adult form of the NoFix Scale (Kanbay, Öztürk, et al., 2025). The higher total explained variance in the adult form indicates that NoFix behaviors develop a more distinct and cognitively structured pattern with age. It is emphasized that the difference in the number of factors and the explained variance ratios depending on developmental stages is an expected situation in the scale development literature (DeVellis, 2014; Worthington & Whittaker, 2006). In this sense, a more integrated two-factor structure in the adolescent form may be explained by the fact that adolescents’ cognitive and emotional processes have not yet fully separated.

Reliability data for the scale revealed that the adolescent form displayed high internal consistency at both the sub-dimension and total score levels. Cronbach’s alpha coefficients above 0.80 indicate good to excellent reliability, based on classical psychometric measurements (Nunnally & Bernstein, 1994). The scale development-related literature reveals that Cronbach’s alpha values above 0.70 are permissible in early-stage scales; however, values above 0.80 indicate strong internal consistency (Hair et al., 2019). Similarly, the fact that the present study reports high McDonald’s Omega coefficients suggests that the items contribute homogeneously to the factor structure. Additionally, the reliability of the scale does not depend solely on the number of items. Reporting the omega coefficient can be considered a methodological choice consistent with contemporary scale development techniques (Dunn et al., 2014).

Regarding construct validity, the AVE and CR values, which meet the recommended thresholds, indicate that the factors explain a satisfactory level of variance and that the measurements are consistent. The fact that the Fornell–Larcker criterion is met, on the other hand, supports the conclusion that there is sufficient inter-factor discrimination and that the scale has discriminant validity (Fornell & Larcker, 1981). The moderate-to-high relationship identified between the obsession and compulsion sub-dimensions means that they are conceptually related but measurably distinguishable. The scale development-related literature emphasizes that moderate inter-factor correlations are expected and theoretically significant, especially in psychological constructs (Brown, 2015).

The conjoint analysis of the fit indices (CFI, TLI, RMSEA, SRMR) for the confirmatory factor analysis reveals that the model displays an acceptable, even excellent level of fit values. RMSEA and SRMR values within the recommended limits prove that the model-data fit is adequate (Hu & Bentler, 1999). A statistically significant chi-square value should also be regarded as an expected occasion in large samples, and this outcome should be interpreted in conjunction with other fit indices (Kline, 2023).

Test–retest reliability data reveal the scale's temporal stability, and NoFix is a relatively continuous digital behavior pattern rather than a temporary state. ICC values above 0.70 indicate a reliability ranging from good to excellent, according to Koo and Li (2016) classification. These findings also align with the high stability values reported in the adult form (Kanbay, Öztürk, et al., 2025), supporting the idea that NoFix is a developmentally consistent construct.

One of the most important findings of this study is that total scale scores differed significantly according to certain descriptive characteristics among adolescents. When the factors contributing to these differences were examined, behavioral tendencies such as immediately checking the smartphone immediately after receiving a notification, keeping the phone constantly on, and feeling uneasy when the phone is set to silent emerged as prominent. These findings indicate that individuals who engage more intensely and continuously with notifications tend to have significantly higher NoFix levels. Considering these self-reported behavioral indicators, it can be suggested that the measurement tool is capable of distinguishing not only cognitive tendencies but also notification-based behavioral patterns. This supports the behavioral sensitivity of the scale and demonstrates that it captures both obsessive thoughts and compulsive control behaviors related to notifications.

In addition to these findings, the results obtained within the scope of criterion validity provide valuable insights into the real-life implications of the scale. The positive and moderate correlations between the NoFix scale and the Digital Amnesia scale indicate that notification-based obsessive thoughts and compulsive checking behaviors may be associated with adolescents' cognitive functioning. It is suggested that notifications generated by digital environments may lead to attentional disruption in adolescents, thereby weakening processes related to information processing and memory. These findings support the criterion validity of the scale and further demonstrate that the NoFix construct represents not only a behavioral tendency but also a comprehensive structure associated with cognitive processes. This finding provides important implications for the protection of adolescent health in the digital age; when considered in light of the existing literature, it highlights the necessity of promoting conscious usage patterns among adolescents (Shabahang et al., 2024).

5. Strengths and limitations

5.1. Strengths

One of the most remarkable strengths of this study is that the development process of the NoFix was carried out using a multi-stage and systematic psychometric approach. Indeed, the study utilized three separate sample sets during the scale development process and also performed multidimensional validity and reliability analyses, including EFA, CFA, internal consistency coefficients, McDonald's Omega, CR, AVE, Fornell–Larcker criterion, and test-retest reliability. In this sense, this study proposes a structure that is not based solely on traditional reliability coefficients and is additionally compatible with contemporary psychometric standards. Furthermore, a two-factor scale structure supported by both EFA and CFA results, as well as high item factor loadings and good explained variance ratios, are crucial findings that strengthen the measurement instrument's structural validity. The high ICC values by test-retest analyses indicate that the scale provides stable measurements over time. Finally, the substantial relationships established with Digital Amnesia provide critical evidence on the scale's external validity.

5.2. Limitations

Despite the comprehensive analyses of the scale's validity and reliability, this study has some limitations. First, the study used a relatively small sample for the test–retest reliability analyses, which may partially limit the generalizability of the temporal stability findings. Additionally, the study data were collected through self-report measures; therefore, the findings may be influenced by potential limitations associated with self-report methodology, such as social desirability effects and respondent bias. Although Harman's single-factor test indicated that common method variance was unlikely to substantially affect the findings, this procedure provides only limited evidence for ruling out common method bias. Therefore, the possibility of residual method effects cannot be completely excluded. Moreover, the reliance on self-report measures without objective smartphone-derived indicators represents another limitation. Future studies should examine the behavioral validity of NoFix by incorporating objective digital data such as notification frequency, smartphone unlocks, screen time, or Digital Wellbeing metrics.

Despite proposing some modification indices in the CFA process, error covariances unsupported by theoretical justification were not included in the model. While this decision maintained the theoretical consistency of the model, it may have contributed to some fit indices approaching boundary values. Furthermore, the cross-sectional design of the study prevents the interpretation of relationships between variables in a causal context. Longitudinal studies analyzing temporal changes in NoFix-related behavioral and psychological variables may provide additional evidence regarding the predictive validity of the scale.

Although the present study provides evidence supporting the validity and reliability of the Boselt NoFix Notification-Checking Obsession Scale–Adolescent Form, discriminant and incremental validity analyses with theoretically related constructs such as FoMO, nomophobia, problematic smartphone use, and smartphone addiction were not conducted. Since the study was carried out with adolescents, the number of measurement tools was intentionally limited to reduce participant burden, prevent questionnaire fatigue, and maintain response quality.

Another limitation concerns construct validation. Although criterion validity was supported through the Digital Amnesia Scale and discriminant validity was established using the Fornell–Larcker criterion, criterion validity was assessed using only a single related construct. Since the study was conducted with adolescents, the number of measurement instruments was intentionally limited to reduce participant burden and maintain response quality. Furthermore, incremental validity was not examined. Future studies should investigate the unique contribution of NoFix beyond related constructs such as FoMO, nomophobia, problematic smartphone use, and smartphone addiction using additional digital behavior measures, the Heterotrait–Monotrait ratio (HTMT), structural equation modeling, and incremental validity analyses. Finally, this study was conducted using a sample from the Turkish population. Therefore, further evaluation of the scale's validity and reliability across different cultural contexts would provide stronger evidence for its cross-cultural validity and make an important contribution to its generalizability.

6. Conclusion

The Boselt NoFix NCOS-AF involves a factor structure developed by considering developmental features, strong reliability and validity indicators, and psychometric findings aligned with the scale development literature. In conclusion, it provides a valid and reliable measurement tool to assess notification-checking obsession in adolescents (Supplementary Files A and B). The fact that it addresses both adolescent and adult forms indicates that the NoFix concept is age-sensitive yet theoretically consistent and significantly contributes to the literature on the developmental dimension of digital behavior. As a result, this study recommends that future research retest the psychometric properties of the scale in various sample groups and use it to analyze digital addiction-related variables.

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Authorship

The all authors made significant contributions to the concept of the article, provided intellectual contribution to the creation of the research design, and interpreted the data. The authors contributed to the drafting of the article and approved the final version of the article. All authors accept responsibility for appropriately investigating and resolving questions related to the accuracy or integrity of any part of the work.

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CRediT: **Deniz S. Yorulmaz Demir**: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing; **Yalçın Kanbay**: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing; **Aysun Akçam**: Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing.

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Data availability statement

The dataset supporting the findings of this study is publicly available in the Zenodo repository. It can be accessed at: https://doi.org/10.5281/zenodo.21539813

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