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Digital Well-Being Scale for Young Adults: Validity and Reliability Study

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ABSTRACT

This study aims to develop a valid and reliable scale to measure digital well-being. The study was conducted in a stepwise process: (1) creating an item pool and ensuring content validity with expert opinion; (2) defining the structure of the scale with exploratory factor analysis; (3) testing the validity of the structure with confirmatory factor analysis (CFA); (4) examining the relationships between the Digital Well-being Scale (DWS) and GWSSF, digital stress, and digital literacy for criterion validity analysis (5) reliability analyses. As a result of EFA, a scale structure consisting of 18 items and four sub-dimensions was obtained. The study presents a multidimensional measurement tool for assessing digital well-being by incorporating self-regulation, digital awareness, meaning, and social relationships in digital contexts. By moving beyond screen time focused indicators, the scale offers a structured framework that can be used in empirical research and applied studies related to digital well-being.

KEYWORDS

Digital well-being; self-regulation; digital awareness; validity; reliability

With digital technologies becoming central to everyday life, their impact on personal well-being has gained growing research attention. Individuals now construct identities, maintain relationships, and fulfill emotional needs through digital environments (Bozkurt & Tu, 2016; Kaya et al., 2025; Ranzini, 2014). This has brought forth the notion of *digital well-being*, referring to how digital engagement influences mental, emotional, and social health. *Digital well-being* involves feeling balanced, safe, and in control while interacting online, maintaining healthy boundaries between online and offline life, and experiencing satisfaction in digital contexts (Jones et al., 2018; Rad & DeMeter, 2019; Vanden Abeele, 2021). Rather than focusing solely on-screen time, current research emphasizes the quality and intentionality of digital engagement—how people regulate their use and derive meaning from it (De Santis & Fantinelli, 2024; Wang & Vella-Brodrick, 2018).

As digital systems become more immersive and persuasive, digital well-being has also emerged as a critical topic within human–computer interaction (HCI). HCI research increasingly demonstrates how interface architectures, notification flows, algorithmic curation, persuasive design elements, and platform affordances influence users' attentional patterns, sense of autonomy, cognitive load, and emotional stability (Gray et al., 2018; Montag & Walla, 2016; Tufekci, 2015). This has led to the development of well-being-centered design and positive computing frameworks aiming to create more balanced and supportive digital experiences (Calvo & Peters, 2014). Understanding digital well-being is therefore essential not only for psychological research but also for evaluating the human impact of design decisions and strengthening user-centered interaction environments.

Beyond the interaction level, global organizations such as the World Health Organization (2021) emphasizes that digital technologies can both enhance access to health services and contribute to psychological strain if used excessively or without balance. The WHO therefore underscores conscious and controlled use as essential for sustaining well-being. Measuring individuals' digital well-being provides

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an evidence base for targeted interventions and policy actions, helping to identify both risks and strengths in digital life.

The concept of digital well-being is intricately linked to various theoretical frameworks in the psychology literature. Among these, Self-Determination Theory (Deci & Ryan, 1985, 2000) posits that individuals' psychological well-being relies on the fulfillment of three fundamental psychological needs: autonomy, competence, and relatedness. Engaging with meaningful content in the digital environment, obtaining online social support and establishing digital boundaries, and developing digital security awareness enable these three basic needs to be met in the digital context.

Theoretical perspectives from psychology enrich this understanding. Self-Determination Theory (Deci & Ryan, 1985, 2000) posits that well-being depends on fulfilling three core needs: autonomy, competence, and relatedness. Meaningful digital interactions, boundary setting, and digital literacy can support these needs. Similarly, Self-Regulation Theory (Baumeister & Vohs, 2007) explains how attention control, content filtering, and time management sustain balanced digital use. The Digital Well-being Framework (Burr et al., 2020) complements these views, highlighting mental balance, emotional stability, social connection, and digital security as interdependent dimensions—echoing WHO's vision of digital health. Identifying stressors such as distraction or social comparison, and developing coping mechanisms, are thus vital for maintaining digital well-being. Positive Psychology's PERMA model (Seligman, 2011) further situates digital well-being within a broader conception of flourishing, including positive emotion, engagement, relationships, meaning, and accomplishment. This lens allows well-being in digital spaces to be assessed not only through harm reduction but also through growth and fulfillment.

Collectively, these frameworks portray digital well-being as a multidimensional construct that integrates protection from digital harms with the promotion of positive functioning online (Islambouli et al., 2025). Previous research has examined digital well-being from several valuable perspectives, each contributing to a growing understanding of this emerging concept. For instance, Kennedy and Baker (2016) introduced the *TechnoWellness Inventory (TWI)* to conceptualize and measure individuals' wellness in relation to their technology use, offering one of the earliest empirical attempts to operationalize the construct within counseling and wellness frameworks. Arslankara et al. (2022) explored digital well-being through the lens of hedonic and eudaimonic happiness, while Gomes et al. (2023) focused on subjective well-being in online settings. Rosič et al. (2024) investigated adolescents' personal experiences with digital life, and Mayiwar et al. (2025) discussed the individual traits associated with digital well-being. Although these studies have enriched the field, many of them were designed for specific age groups or emphasized only certain aspects—such as happiness, self-control, or safe use—rather than addressing the construct in its full complexity. Across these tools, dimensions such as meaningful participation, online social support, digital self-regulation, and security awareness rarely appear together within a unified framework. These gaps highlight the need for a more comprehensive, psychologically grounded, and HCI-informed measure suitable for adult users.

In this study, digital well-being is conceptualized as the individual's capacity to engage with digital technologies in a balanced, purposeful, and secure manner that supports psychological, social, and emotional health (Büchi, 2024; Burr et al., 2020; World Health Organization, 2021). This conceptualization is theoretically grounded in the PERMA model of well-being (Seligman, 2011), Self-Regulation Theory (Baumeister & Vohs, 2007), and the Digital Well-being Framework (Burr et al., 2020), which together provide the foundation for developing and interpreting the dimensions of the proposed scale. Guided by the PERMA model, Self-Regulation Theory, and the Digital Well-being Framework, the study aims to develop and validate a theoretically grounded scale for assessing digital well-being. Specifically, it addresses two questions:

1. Can digital well-being be structured as a multidimensional construct from both theoretical and empirical perspectives?
2. Does the developed scale demonstrate robust psychometric validity and reliability?

1. Method

This research was conducted with the aim of developing a valid and reliable measurement tool for the concept of digital well-being by addressing it in a multidimensional structure. The scale development process was structured based on DeVellis (2016) eight-step scale development model. Within the scope of the process, the concept of digital well-being was first defined within a theoretical framework, followed by the creation of a comprehensive item pool based on this definition. Subsequently, content validity was assessed based on expert opinions, and comprehensive statistical analyses (item analysis, factor analyses, reliability analyses, etc.) were conducted using preliminary application data to test the psychometric properties of the scale.

1.1. Participants and procedure

Before the study began, ethical approval was obtained from the researcher's institution. All participants were provided with the necessary information about the purpose of the study and ethical considerations. Their consent was obtained through an informed consent form.

The criteria for participation in the study were being over 18 years of age, owning at least one digital device, and using the digital device for purposes other than work or homework. The following steps were followed in the study, and scales were sent to different research groups for each stage. Thus, analyses were performed on the data of a total of 1182 people. Participants were primarily young adults. Data for the Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and criterion-related validity analyses were obtained from three independent samples to ensure methodological rigor. The EFA was conducted on data obtained from 370 participants; after removing 20 multivariate outliers based on Mahalanobis distance ($p < 0.001$), analyses were carried out on 350 observations. The CFA was performed on a separate sample of 293 participants, with 16 multivariate outliers excluded (final $N = 277$). Criterion-related validity was examined using an independent sample of 271 participants and further validated with a second independent sample of 284 participants. This design ensured that each phase of the validation process was based on distinct datasets, thereby minimizing common-method bias and supporting the robustness and generalizability of the findings. Information about the participants in each stage and the analyses performed is presented below (see Figure 1):

1.1.1. Stage 1: Item pool and expert opinions

The structure to be measured has been theoretically defined to include the psychological, social, and behavioral dimensions of individuals' relationships with digital technologies. This definition process is based on primarily Self-Determination Theory (Deci & Ryan, 2000) and contemporary approaches in the digital well-being literature (Burr et al., 2020; Hatem & Ker, 2021). According to Self-Determination Theory, individuals' ability to maintain their autonomy in the digital environment, sustain their sense of competence, and build meaningful social relationships are the determining factors of their digital well-being levels. In addition, Self-Regulation Theory (Baumeister & Vohs, 2007) highlights processes such as attention control, time management, and purposeful use in individuals' interactions with digital content. The Digital Well-being Framework (Burr et al., 2020) focuses on how individuals establish balance in areas such as mental stability, emotional well-being, social connection, and digital security. In addition, Seligman's (2011) PERMA Model also interprets digital well-being in the context of positive psychology and allows for the evaluation of individuals' experiences of meaning, engagement, relationships in the digital environment. In line with this theoretical foundation, a pool of 30 preliminary items was created. During this process, existing digital well-being scales were also examined to ensure conceptual coverage and identify theoretical gaps. Previous measures such as the Digital Well-Being Scale (Arslankara et al., 2022), Design and Validation of the Digital Well-Being Scale (Gomes et al., 2023), the Perceived Digital Well-Being in Adolescence Scale (Rosić et al., 2024), and the TechnoWellness Inventory (Kennedy & Baker, 2016) were reviewed. Additionally, the conceptual model proposed by Mayiwar et al. (2025) was evaluated. These instruments provided useful insights. The present scale incorporates both protection-oriented dimensions (eg, digital security, risk awareness) and growth-oriented dimensions (eg, meaningful participation, self-regulation, social supports), offering a

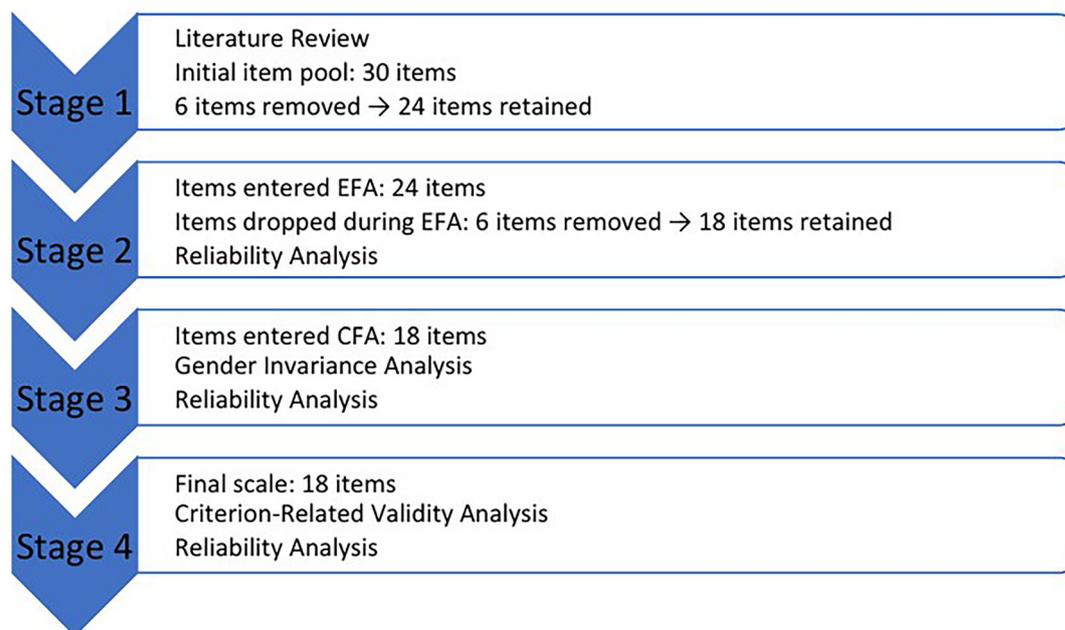


Figure 1. Flow of scale development process.

structure that is broader than existing instruments and directly informed by psychological and HCI models. The item pool was reviewed by five experts in the field. The initial pool of 30 items was reviewed by a panel of five experts to ensure content relevance and conceptual clarity. The panel consisted of one expert with a Ph.D. in Educational Measurement and Evaluation, two psychologists with doctoral degrees, and two guidance and psychological counseling specialists who hold doctoral degrees and have expertise in both cyberpsychology and positive psychology. This expert composition was intended to cover the domains of psychological assessment, digital behavior, and well-being. Each expert independently evaluated the items using a three-point relevance scale (“unnecessary,” “useful but not necessary,” and “necessary”). Content validity ratios (CVR) were calculated using the Lawshe (1975) method, which determines the degree of expert agreement on whether each item is essential for representing the construct. In this approach, experts rate each item as “unnecessary,” “useful but not necessary,” or “necessary,” and five items with CVR values below 0.99 were discarded from the scale. Five items were excluded based on CVR analysis, and one additional item (I16) was removed prior to EFA due to item-level screening. Therefore, EFA was conducted on 24 items. All items were rated on a four-point Likert scale (1 = strongly disagree, 4 = strongly agree).

1.1.2. Stage 2: Exploratory factor analysis (EFA)

Data was collected from 370 university students for the EFA. However, based on the Mahalanobis distance, 20 outliers were removed from the data set as they were found to be significant at the $p < 0.001$ level in the multivariate outlier analysis based on Mahalanobis distance, and analyses were conducted on the remaining 350 observations. The average age of the participants was 22.8 ($SD = 6.41$); 74% (259) were female, and 26% (91) were male. The majority of socioeconomic levels (87.1%) were reported as middle, 10.6% (37) as low, and 2.29% (8) as high. When evaluated in terms of weekly screen time, 21.1% ($n = 74$) of participants had low levels (1–3 hrs), 51.4% ($n = 180$) had moderate levels (4–6 hrs), and 27.4% ($n = 96$) had high levels (7 hrs or more) of screen use. This distribution indicates that the majority of the sample had weekly screen time concentrated in the 4–6 hrs range. When weekend screen time data was examined, 28.3% of participants ($n = 99$) reported low levels (1–4 hrs), 41.3% ($n = 144$) reported moderate levels (5–8 hrs), and 30.4% ($n = 105$) reported high levels (9 hrs or more). It is observed that screen time increases on weekends and that approximately one-third of participants spend more than 9 hrs in front of digital screens. The suitability of the data for factor analysis was evaluated using the Kaiser-Meyer-Olkin (KMO) and Bartlett’s sphericity tests. The analyses were conducted using the Unweighted Least Squares (ULS) factor extraction and Oblimin rotation methods. Oblimin

rotation was used, as the dimensions of digital well-being were theoretically assumed to be correlated. The Oblimin rotation provides a more accurate solution for psychological constructs where latent factors are conceptually interdependent (Costello & Osborne, 2005; Fabrigar et al., 1999). The Unweighted Least Squares (ULS) extraction method was employed because it does not require the assumption of multivariate normality and provides robust factor solutions when data distributions are non-normal or ordinal in nature. Given the ordinal scaling of the Likert-type items and to obtain robust parameter estimates under departures from multivariate normality (Flora & Curran, 2004; Mindrila, 2010).

1.1.3. Stage 3: Confirmatory factor analysis (CFA)

From the sample of 293 participants who took part in the confirmatory factor analysis, 16 outliers were removed based on Mahalanobis distance ($p < 0.001$), and the analyses were conducted on 277 individuals. Thus, the research group consisted of a total of 277 young adults aged between 18 and 24, with an average age of 21.4 ($SD = 1.75$). Of the participants, 51.3% ($n = 142$) were female and 48.7% ($n = 135$) were male. When examining the distribution according to educational status, it was found that the majority of participants were university students (77.6%; $n = 215$), while the remainder were bachelor's degree holders (22.4%; $n = 62$). In terms of socioeconomic status, 77.3% ($n = 214$) of participants identified themselves as middle class, 11.6% ($n = 32$) as upper class, and 11.2% ($n = 31$) as lower class. In terms of weekday digital device usage time, 5.05% of participants ($n = 14$) reported low usage (0–3 hrs), 70.1% ($n = 194$) reported moderate usage (3–5 hrs), and 24.8% ($n = 69$) reported high usage (5 hrs or more). This distribution indicates that the majority of the sample concentrated their weekday screen time in the 3–5 hrs range. When weekend usage times were examined, 2.53% of participants ($n = 7$) reported low levels (0–3 hrs), 46.2% ($n = 128$) reported moderate usage (3–5 hrs), and 51.6% ($n = 142$) reported high usage (5 hrs or more). This finding indicates that digital usage on weekends is significantly longer than on weekdays. CFA was applied using the Diagonally Weighted Least Squares (DWLS) estimator. Additionally, internal consistency reliability was assessed using Cronbach's alpha coefficient.

1.1.4. Stage 4: Criterion-related validity

The study group for criterion-related validity analyses consisted of 271 participants. The participants' ages ranged from 18 to 30, with an average age of 21.88 ($SD = 3.06$). 51.3% of the participants ($n = 139$) are female and 48.7% ($n = 132$) are male. When examining the educational levels of the participants, it is seen that the majority are university students (81.9%; $n = 222$). 9.96% of participants were high school graduates ($n = 27$), 7.01% were bachelor's degree graduates ($n = 19$), and 1.11% were elementary school graduates ($n = 3$). When examining data related to socioeconomic status (SES), it was determined that 80.8% of participants had a medium SES ($n = 219$), 17% had a low SES ($n = 46$), and 2.2% had a high SES ($n = 6$). For criterion-related validity, the correlation between the General Well-Being Scale (Odacı et al., 2021), Multidimensional Digital Stress Scale (Erinç, 2023), and Digital Literacy Scale (Bayrakçı & Narmanlioğlu, 2021) and the developed scale was examined. Additionally, internal consistency reliability was assessed using Cronbach's alpha.

A separate sample of 284 participants was used to further cross-validate the criterion-related findings. A total of 284 university students participated in the study. Participants' ages ranged from 18 to 26 years ($M = 20.26$, $SD = 2.00$), with a median age of 20. In terms of gender, 203 participants (71.5%) were female, 80 (28.2%) were male, and 1 participant (0.4%) preferred not to disclose their gender. Daily screen time, which included the use of computers, tablets, phones, and televisions, was grouped into three categories: low screen time (1–3 hrs) reported by 29 participants (10.2%), moderate screen time (4–6 hrs) reported by 185 participants (65.1%), and high screen time (7 hrs or more) reported by 70 participants (24.6%).

2. Measures

2.1. General Well-Being Scale Short Form (GWSSF)

In this study, the General Well-Being Scale—Short Form (GWSSF) was used within the scope of criterion-related validity analyses. The original version of the scale was developed by Longo et al. (2017,

2018). The scale consists of 14 items and is a five-point Likert scale. This scale has a single-factor structure. The adaptation to Turkish was carried out by Odacı et al. (2021). During the adaptation process, confirmatory factor analysis confirmed the scale's unidimensional structure; construct validity and criterion-related validity were supported. $\chi^2/df = 4.49$, CFI = 0.93, NFI = 0.92, RMSEA = 0.086, SRMR = 0.066). The scale's internal consistency ($\alpha = 0.84$), construct reliability (0.84), and split-half test correlation (0.77) were found to be high. It was determined that GWSSF scores showed significant positive correlations with life satisfaction, positive affect, and need satisfaction, and significant negative correlations with negative affect. In the current study, the GWSSF scale demonstrated high internal consistency, with Cronbach's alpha calculated as $\alpha = 0.906$.

2.2. Digital Literacy Scale (DLS)

The Digital Literacy Scale was used in the present study to assess participants' digital literacy and to examine its association with digital well-being indicators. The original scale was developed by Bayrakçı and Narmanlıoğlu (2021). The final version of the Digital Literacy Scale consists of 29 items rated on a five-point Likert-type scale and demonstrates a six-factor structure: Ethics and Responsibility, General Knowledge and Functional Skills, Daily Use, Advanced Production, Privacy and Security, and Social Dimension. Exploratory factor analysis supported a six-factor solution that explained 61.84% of the total variance, with factor loadings generally above 0.30. Confirmatory factor analysis using an independent sample indicated acceptable model fit (eg, $\chi^2/df = 4.35$, GFI = 0.92, CFI = 0.91, RMSEA = 0.051), suggesting that the six-factor model adequately represents the latent structure of digital literacy. Internal consistency estimates were acceptable to high for all subscales (Cronbach's α ranging from 0.72 to 0.88) and excellent for the total scale ($\alpha = 0.91$), indicating that the measure demonstrates adequate reliability for research use. In the current study, the DLS scale demonstrated high internal consistency, with Cronbach's alpha calculated as $\alpha = 0.927$.

2.3. Multidimensional Digital Stress Scale (MDSS)

The Multidimensional Digital Stress Scale was used within the scope of criterion-related validity analyses. The original scale was developed by Hall et al. (2021) to capture distinct dimensions of stress experienced in online and technology-mediated contexts. The instrument consists of 24 items rated on a five-point Likert-type scale and includes five subdimensions: *Accessibility Stress*, *Approval Anxiety*, *Fear of Missing Out (FoMO)*, *Connection Overload*, and *Online Vigilance*. The Turkish adaptation of the MDSS was carried out by Erinç (2023). Confirmatory factor analysis indicated an adequate model fit ($\chi^2/df = 2.12$, $p < 0.001$; RMSEA = 0.061, CFI = 0.951, NFI = 0.920), confirming the structural validity of the Turkish version. The overall internal-consistency coefficient was $\alpha = 0.95$, with subscale alphas ranging from 0.89 to 0.94, demonstrating excellent reliability. In the current study, the MDSS scale demonstrated high internal consistency, with Cronbach's alpha calculated as $\alpha = 0.914$.

3. Data analysis

In the study, the data analysis process was structured in multiple stages to evaluate the psychometric properties of the measurement tool. First, the normality assumption was tested at both the univariate and multivariate levels. In assessing univariate normality, skewness and kurtosis values were considered. In this context, skewness and kurtosis coefficients within the ± 2 range indicate that the data are close to a normal distribution (Kline, 2015).

To assess construct validity, exploratory factor analysis (EFA) was first applied. This analysis was conducted using the Unweighted Least Squares (ULS) method and focused on revealing the common factor structure rather than the principal components. Prerequisites such as the Kaiser-Meyer-Olkin (KMO) adequacy test and Bartlett's Sphericity Test were evaluated in determining the factor structure (Field, 2018).

The structure obtained after EFA was subjected to group-based structural equation modeling to test measurement invariance across different gender groups. In this context, comparisons were made at the

levels of structural invariance, factor loading invariance (measurement invariance), and residual variance invariance (Milfont & Fischer, 2010).

The multivariate normality assumption was tested using Mardia's multivariate skewness and kurtosis test (Mardia, 1970). If Mardia's kurtosis value was found to be significant, robust estimators were used instead of the classical Maximum Likelihood estimator in confirmatory factor analysis (CFA). Confirmatory factor analysis (CFA) was conducted to test the theoretical validity of the four-factor structure obtained. In the CFA analysis, the Diagonally Weighted Least Squares (DWLS) estimation method was preferred, as it is known to provide more reliable results under the assumption that the data are not normally distributed (Li, 2016). The model's fit was evaluated using basic fit indices such as CFI (Comparative Fit Index), TLI (Tucker-Lewis Index), RMSEA (Root Mean Square Error of Approximation), and SRMR (Standardized Root Mean Square Residual). CFI and TLI values above 0.90 and RMSEA and SRMR values below 0.08 indicate that the model shows an acceptable level of fit (Hu & Bentler, 1999).

The reliability analyses of the scale were conducted in a multifaceted manner. Internal consistency was calculated using Cronbach's α coefficient. This comprehensive analysis demonstrated that the scale provides consistent and reliable measurements. Finally, to assess criterion-related validity, a Pearson correlation analysis was conducted between the Digital Well-Being Scale and the GWSSF. The positive and significant correlations obtained support the external validity of the developed scale.

All analyses were performed using RStudio version 2024.05.1. The FAFa package (Kılıç, 2024), OpenMx (Neale et al., 2016), and lavaan R (Rosseel, 2012) packages were used for exploratory factor analysis (EFA), confirmatory factor analysis (CFA), gender-based measurement invariance analysis, and reliability analyses. Descriptive statistics and correlation analyses were conducted using the psych package (Revelle, 2023).

4. Results

4.1. Exploratory factor analysis (EFA)

Before proceeding with the analyses, basic statistics and assumptions related to the scale items were tested. In this context, the arithmetic mean, standard deviation, skewness, and kurtosis values were calculated for each item. Before proceeding with exploratory factor analysis (EFA), the normality of the distribution of item scores was examined. It was observed that the skewness and kurtosis values ranged from -0.66 to 0.01 and -0.47 to 1.75 , respectively. Since these values fell within the ± 2 range (Kline, 2015), it was accepted that the data exhibited a distribution close to normal and was suitable for parametric analyses. Additionally, it was determined that the item means ranged from 2.46 to 3.16 and did not show a significant deviation in terms of central tendency. Details regarding these values are presented in Table 1.

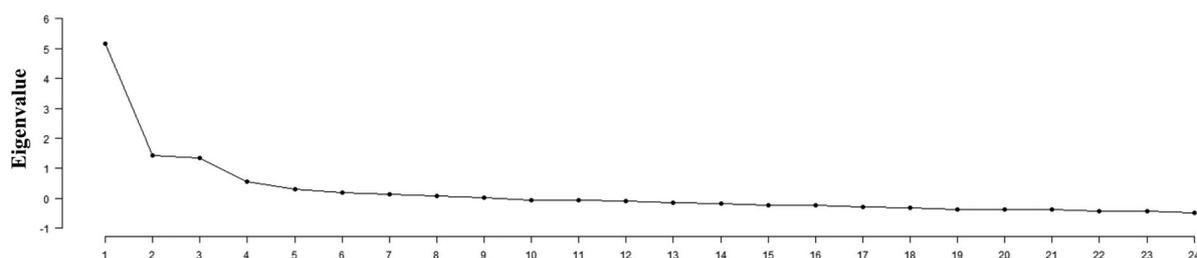
The traditional parallel analysis method was used to determine the number of factors to be extracted in the exploratory factor analysis. This method suggested a four-factor structure. This finding was also supported by the scree plot. In the graph, the eigenvalues of the factors showed a significant decline starting from the fifth factor, indicating that a four-factor structure is appropriate according to the "elbow point" criterion. The relevant graph is presented visually in Figure 2 of the study.

Polychoric correlations were preferred as the correlation matrix type in exploratory factor analysis. The Unweighted Least Squares (ULS) method was used as the factor extraction method; this method is accepted in the literature as a recommended approach, especially for data that are not normally distributed. For the rotation process, Oblimin (oblique) rotation was applied, which allows for correlations between factors. This assumed that the obtained factors could be related to each other, and the analysis was conducted based on this structure.

Before proceeding to exploratory factor analysis, the suitability of the data for analysis was evaluated using the Kaiser-Meyer-Olkin (KMO) sample adequacy test and Bartlett's sphericity test. The KMO coefficient was found to be 0.853 , which, according to Field (2018), indicates "very good" (meritorious) sample adequacy. The Bartlett sphericity test result was also found to be significant ($\chi^2(276) = 4000.51$, $p < 0.001$), indicating that the correlations between the items were at a level suitable for factor analysis.

Table 1. Descriptive statistics of the items.

Items	Min	Max	Median	Mean	Skewness	Kurtosis
I1	1.00	4.00	3.00	2.94	-0.57	0.89
I2	1.00	4.00	3.00	3.00	-0.52	1.15
I3	1.00	4.00	3.00	2.64	-0.35	-0.10
I4	1.00	4.00	3.00	2.88	-0.35	0.65
I5	1.00	4.00	3.00	2.84	-0.32	0.35
I6	1.00	4.00	3.00	2.78	-0.16	-0.00
I7	1.00	4.00	3.00	2.72	-0.17	-0.09
I8	1.00	4.00	3.00	2.92	-0.35	0.12
I9	1.00	4.00	3.00	3.07	-0.53	0.90
I10	1.00	4.00	2.00	2.01	0.55	-0.25
I11	1.00	4.00	3.00	2.78	-0.52	0.43
I12	1.00	4.00	3.00	2.65	-0.04	-0.42
I13	1.00	4.00	3.00	2.72	-0.41	0.17
I14	1.00	4.00	2.00	2.38	0.09	-0.63
I15	1.00	4.00	3.00	2.85	-0.89	1.55
I17	1.00	4.00	3.00	2.74	-0.38	0.24
I18	1.00	4.00	3.00	2.72	-0.30	0.08
I19	1.00	4.00	2.00	2.46	0.01	-0.47
I20	1.00	4.00	3.00	2.68	-0.31	-0.19
I21	1.00	4.00	3.00	2.86	-0.41	0.15
I22	1.00	4.00	3.00	2.94	-0.39	0.35
I23	1.00	4.00	3.00	3.16	-0.66	1.75
I24	1.00	4.00	3.00	3.02	-0.47	0.40
I25	1.00	4.00	3.00	3.14	-0.51	1.09

**Figure 2.** Scree plot with EFA-determined eigenvalues.

These results demonstrate that the data meet the necessary assumptions for factor analysis. Before proceeding to exploratory factor analysis, sample adequacy was also evaluated at the item level. According to the criteria proposed by Ferrando and Lorenzo-Seva (2021), KMO (MSA) values below 0.50 may require exclusion from the analysis due to insufficient variance sharing. In this study, the individual KMO values of all items ranged from 0.63 to 0.90 (Table 2). This finding indicates that each item has sufficient common variance to remain in the analysis and is suitable for factor analysis.

Prior to exploratory factor analysis, the item-item correlation matrix was visualized to examine the general structure of the relationships between items. This visualization clearly reveals item pairs with high correlations (eg, I2–I3 and I23–I24) and supports a correlation structure suitable for factor analysis. This correlation structure meets one of the basic assumptions of factor analysis, namely the condition of inter-variable relationships (Tabachnick & Fidell, 2013). The factor loadings of the 24 items are presented in Table 2. As a result of exploratory factor analysis, a total of six items (I1, I8, I9, I10, I14, I15) with factor loadings below 0.40 and/or high loadings on more than one factor were excluded from the analysis. After excluding items I1, I8, I9, I10, I14, and I15, the exploratory factor analyses were conducted again. The factor loadings of the remaining 18 items are presented in Table 3. The relevant heat map is presented in Figure 3 (Item labels reflect pre-renumbering codes).

As a result of exploratory factor analysis (with 18 items), factor loadings showing the relationship of each item with the four-factor structure were obtained. In the analysis, items with factor loadings of 0.40 or above were considered significant (Costello & Osborne, 2005). Inspection of the factor loadings indicated a clear four-factor structure. Factors are described according to the relative magnitude of their item loadings rather than item numbering. To avoid confusion, all subsequent analyses refer to the

Table 2. Item factor loadings and communalities (h^2) for 24 items.

Items	ULS1	ULS2	ULS3	ULS4	h2_communality
I1	0.20	0.03	0.30	0.11	0.24
I2	0.53	-0.01	0.25	-0.01	0.44
I3	0.46	0.33	-0.01	0.16	0.56
I4	0.72	-0.10	0.12	0.04	0.58
I5	0.54	0.03	0.15	0.13	0.49
I6	0.87	0.05	-0.09	-0.00	0.74
I7	0.66	0.07	-0.06	0.14	0.56
I8	-0.10	-0.30	0.14	0.28	0.17
I9	0.32	0.28	0.24	-0.19	0.35
I10	-0.06	0.21	-0.24	0.48	0.26
I11	0.20	0.56	0.18	-0.08	0.52
I12	0.07	0.70	-0.01	0.01	0.55
I13	-0.02	0.75	0.06	-0.03	0.56
I14	-0.09	0.61	-0.09	0.11	0.35
I15	-0.17	0.07	0.06	0.45	0.18
I17	0.10	-0.02	0.07	0.64	0.50
I18	0.08	0.02	0.07	0.64	0.49
I19	0.06	-0.10	-0.01	0.71	0.53
I20	0.04	0.04	0.10	0.64	0.49
I21	0.09	0.07	0.51	0.10	0.37
I22	0.09	-0.02	0.67	0.01	0.51
I23	-0.02	0.05	0.71	0.04	0.52
I24	-0.08	0.10	0.79	0.06	0.63
I25	0.03	-0.08	0.80	-0.02	0.64

Table 3. Item factor loadings and communalities (h^2) for 18 items.

Items	New items labels	Min	Max	Median	Mean	Skewness	Kurtosis
I2	I1	1.00	4.00	3.00	3.01	-0.47	1.31
I3	I2	1.00	4.00	3.00	2.63	-0.41	-0.04
I4	I3	1.00	4.00	3.00	2.89	-0.27	0.54
I5	I4	1.00	4.00	3.00	2.85	-0.31	0.44
I6	I5	1.00	4.00	3.00	2.79	-0.14	0.00
I7	I6	1.00	4.00	3.00	2.71	-0.18	-0.04
I11	I7	1.00	4.00	3.00	2.80	-0.47	0.49
I12	I8	1.00	4.00	3.00	2.64	-0.01	-0.37
I13	I9	1.00	4.00	3.00	2.74	-0.38	0.22
I17	I10	1.00	4.00	3.00	2.72	-0.40	0.30
I18	I11	1.00	4.00	3.00	2.71	-0.31	0.13
I19	I12	1.00	4.00	2.00	2.45	0.00	-0.40
I20	I13	1.00	4.00	3.00	2.65	-0.37	-0.06
I21	I14	1.00	4.00	3.00	2.86	-0.36	0.23
I22	I15	1.00	4.00	3.00	2.94	-0.28	0.38
I23	I16	1.00	4.00	3.00	3.16	-0.37	1.56
I24	I17	1.00	4.00	3.00	3.04	-0.29	0.28
I25	I18	1.00	4.00	3.00	3.15	-0.39	1.03

Notes: Item numbering was revised after confirmatory factor analysis (CFA) to reflect the final 18-item structure. The "Items" column shows the original item labels from the EFA stage, whereas the "New Items Names" column presents the renumbered item labels used in CFA and subsequent analyses.

renumbered items (see Table 3). From this point onward, the renumbered item codes are used. The first factor (ULS1) was primarily defined by items I2, I3, I4, I5, I6, and I7. Among these, items I6 (0.81) and I7 (0.83) demonstrated the strongest loadings, accompanied by relatively high communalities, indicating that they were well explained by the extracted factor. The remaining items within this factor showed moderate to strong loadings ranging from 0.50 to 0.71. The second factor (ULS2) consisted of items I21, I22, I23, I24, and I25. Within this set, items I24 (0.89) and I25 (0.90) exhibited exceptionally strong loadings and high communalities, whereas item I21 showed a comparatively lower but still meaningful loading (0.54). The third factor (ULS3) was characterized by items I17, I18, I19, and I20. Items I17 (0.81) and I18 (0.83) loaded most strongly on this factor, while I19 (0.63) and I20 (0.64) demonstrated moderate but acceptable loadings. Communalities for this factor ranged from 0.44 to 0.69, suggesting that a substantial proportion of item variance was accounted for by the latent construct. The fourth factor (ULS4) was represented by items I11, I12, and I13. Items I12 (0.80) and I13 (0.82) yielded the highest loadings within this factor, whereas item I11 showed a more modest but still acceptable loading (0.54). Overall, the loading pattern indicated that items clustered cleanly under their

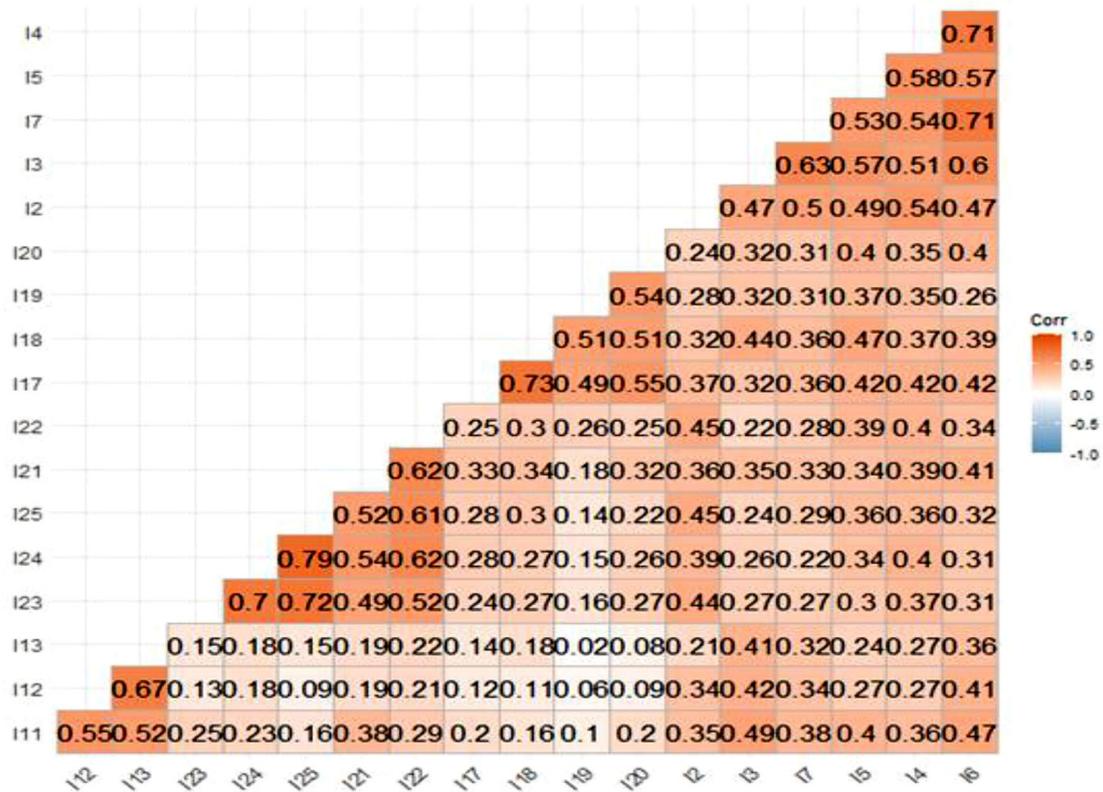


Figure 3. Heatmap of the inter-item correlation matrix (18 items). Note: Each cell represents the polychoric correlation between two items, with color intensity indicating the strength of the association.

respective factors, and communalities remained within acceptable ranges, providing strong support for the proposed four-factor structure.

The correlations among the four latent factors indicated that the dimensions were related but not redundant. The strongest association emerged between F1 and F3 ($r=0.57$), followed by the correlations between F1 and F2 ($r=0.45$) and F1 and F4 ($r=0.50$). In contrast, the weakest relationship was observed between F3 and F4 ($r=0.17$). These values suggest a pattern in which the factors share moderate common variance while still retaining distinguishable conceptual boundaries. The analysis of explained variance further supported the adequacy of the four-factor structure. The first factor (ULS1) accounted for 18% of the total variance, closely followed by ULS2, which also explained 18%. ULS3 contributed an additional 14%, and ULS4 explained 10%, bringing the cumulative variance explained by the four factors to 60%. When considering only the proportion of variance attributed to the extracted factors, ULS1 accounted for 31%, ULS2 for 30%, ULS3 for 22%, and ULS4 for 17%, reaching a cumulative proportion of 100%. This distribution indicates that each factor contributes meaningfully to the overall structure, with no single factor disproportionately dominating the model.

Corrected item–total correlations were examined to evaluate the contribution of each item to the overall scale and its subdimensions. As shown in Table 4, the items generally demonstrated moderate to strong associations with their respective factors, indicating that they align well with the underlying constructs. The coefficients also supported the internal consistency of the four-factor structure, with no item falling below commonly accepted thresholds for scale development.

Examination of the corrected item–total correlations indicates that the scale demonstrates a coherent internal structure aligned with its four-factor model. Across the full scale, correlations ranged from 0.314 to 0.581, suggesting that most items show moderate to strong relationships with the overall construct. The highest values were observed for items within Factor 1, where correlations reached up to 0.581 (I6), reflecting the central contribution of these items to the general scale structure. Within Factor 1, the item–total correlations (0.516–0.657) suggest strong internal consistency. Items I6 and I7

Table 4. Corrected item–total correlations for the total scale and subscales.

Item	Total scale	Factor 1	Factor 2	Factor 3	Factor 4
I1	0.522	0.516			
I2	0.569	0.572			
I3	0.552	0.586			
I4	0.546	0.555			
I5	0.581	0.657			
I6	0.551	0.615			
I14	0.424		0.457		
I15	0.463		0.577		
I16	0.425		0.569		
I17	0.482		0.635		
I18	0.402		0.585		
I10	0.423			0.556	
I11	0.423			0.532	
I12	0.396			0.540	
I13	0.411			0.533	
I7	0.427				0.493
I8	0.388				0.576
I9	0.314				0.576

Notes: Factor 1: Meaningful and Purposeful Digital Participation, Factor 2: Digital Security and Awareness, Factor 3: Digital Social Support and Relationships, Factor: 4 Digital Self-Regulation. Item labels in this table are based on the renumbered item codes derived after confirmatory factor analysis (CFA). For clarity, original item numbers used prior to CFA are reported in Table 3. All subsequent analyses and tables in the manuscript follow the new item numbering.

emerged as the most robust indicators of this dimension, whereas I2 showed the lowest correlation within the factor but still within an acceptable range. Items belonging to Factor 2 also demonstrated solid performance, with correlations ranging from 0.457 to 0.635. Notably, I24 showed the strongest relationship with the subscale total (0.635), indicating that it is a key item representing digital self-regulation behaviors such as time management and boundary setting. For Factor 3, item–total correlations were consistently moderate (0.532–0.556). Within Factor 4, item–total correlations ranged from 0.493 to 0.576. Items I12 and I13 showed relatively stronger associations with the subscale total, whereas I11 demonstrated the weakest contribution to this factor, though still within acceptable psychometric limits. Overall, the pattern of correlations indicates that the majority of items adequately represent their respective latent dimensions and contribute meaningfully to the reliability of both the subscales and the overall measure. No item falls below commonly accepted thresholds (eg, 0.30), suggesting that all items can be retained without compromising internal consistency.

Taken together, the factor correlations and variance estimates provide coherent support for the proposed four-factor solution. According to the EFA results, the 18-item scale showed a four-factor structure. Each factor was conceptually named according to the content of the loaded items:

4.1.1. Factor 1—Meaningful and purposeful digital participation

This factor is represented by items I2, I3, I4, I5, I6, and I7, reflecting individuals' perceptions of their interactions with digital technologies as productive, value-oriented, satisfying, and consistent with their life goals. This dimension indicates that individuals use digital environments not merely to pass time but to make meaningful contributions.

4.1.2. Factor 2—Digital security and awareness

Items I21, I22, I23, I24, and I25 are included in this factor and reflect the extent to which individuals believe they can protect themselves against threats they may encounter in the digital environment. The ability to respond to cyberbullying, personal data security, and the ability to distinguish digital risks are addressed in this factor.

4.1.3. Factor 3—Digital social support and relationships

This dimension includes items I17, I18, I19, and I20. This factor represents the level of social support individuals receive, emotional sharing they experience, and how valued they feel in the relationships they establish through digital environments.

4.1.4. Factor 4—Digital self-regulation

This factor includes items I11, I12, and I13. Participants' self-regulation skills regarding the extent to which they use digital technologies in a planned, limited, and purposeful manner are grouped under this dimension. It covers topics such as time management, attention control, and setting digital boundaries.

The naming of the four factors obtained from the EFA was informed by theoretical frameworks in digital well-being and positive psychology. The first factor, *Meaningful and Purposeful Digital Participation*, captures the eudaimonic aspects of digital engagement aligned with the PERMA model (Seligman, 2011) and Self-Determination Theory (Deci & Ryan, 2000). The second factor, *Digital Security and Awareness*, represents awareness and safety aspects consistent with the Digital Well-Being Framework (Burr et al., 2020). The third factor, *Digital Social Support and Relationships*, corresponds to the relatedness component of Self-Determination Theory and the relational dimension of digital well-being. The fourth factor, *Digital Self-Regulation*, reflects the control and management of digital behaviors described in Self-Regulation Theory (Baumeister & Vohs, 2007). Thus, factor names were conceptually grounded rather than purely data-driven.

The final 18-item structure obtained from the EFA was subsequently tested using Confirmatory Factor Analysis (CFA) to verify the model fit and confirm the four-factor structure. The criterion-related validity was then examined by correlating the scale scores with an external measure of general well-being.

4.2. Confirmatory factor analysis (CFA)

Prior to confirmatory factor analysis (CFA), basic descriptive statistics for the 18 items of the scale were examined. The mean scores for the items ranged from 2.43 (Item 12) to 3.16 (Item 16). The median value for all items was 3.00, indicating that the distribution was generally concentrated around the mean values. Skewness values ranged from -0.46 to 0.01 , while kurtosis values ranged from -0.39 to 1.31 . These values indicate that the data are close to a normal distribution at the univariate level (Kline, 2015).

However, the multivariate normality assumption was also evaluated. According to the results of Mardia's Skewness test (Skewness = 1959.19, $p < 0.001$) and Kurtosis test (Kurtosis = 23.55, $p < 0.001$), the multivariate normal distribution assumption was violated. Similarly, the results of the Energy Test ($E = 4.74$, $p < 0.001$) also indicate that this assumption is not met. Therefore, Diagonally Weighted Least Squares (DWLS), a method that is insensitive to the assumption of multivariate normality and is particularly recommended for ordinal-scaled data, was used as the estimation method in confirmatory factor analysis (Li, 2016).

When examining the fit indices related to confirmatory factor analysis (CFA), it is seen that the model fits the data quite well. The chi-square value is 196.395, which is significant with 129 degrees of freedom ($p < 0.001$). However, it is known that the chi-square test alone is not a sufficient criterion due to its sensitivity to sample size (Brown, 2015). Therefore, additional fit indices were also evaluated. The chi-square/df ratio was found to be 1.522, and since this value is below 2, it indicates a good fit. The Comparative Fit Index (CFI) was calculated as 0.994 and the Tucker–Lewis Index (TLI) as 0.993; these values indicate excellent fit, as they are above 0.95 (Hu & Bentler, 1999). The Root Mean Square Error of Approximation (RMSEA) was 0.044, with a 90% confidence interval ranging from 0.031 to 0.055; this interval indicates that the model remains within acceptable limits. The Standardized Root Mean Square Residual (SRMR) value was found to be 0.049 and remained below the 0.08 threshold, indicating good fit. All these findings indicate that the four-factor structure of the scale developed based on confirmatory factor analysis aligns highly with the data and has strong structural validity.

In the confirmatory factor analysis, standardized factor loadings were examined to evaluate the strength of the relationships between the latent constructs and their observed indicators (see Table 3). All factor loadings were statistically significant ($p < 0.001$), indicating that the observed variables were meaningful indicators of their respective latent dimensions.

For the Meaningful and Purposeful Digital Participation factor, standardized loadings ranged from 0.70 to 0.83, reflecting strong associations between the items and the latent construct. These values

indicate that the items consistently capture purposeful, value-oriented, and satisfying digital engagement. Items loading on the Digital Security and Awareness factor demonstrated standardized loadings between 0.73 and 0.87, suggesting that this dimension is well defined by indicators related to digital safety, risk awareness, and protective behaviors in digital environments. The Digital Social Support and Relationships factor showed standardized loadings ranging from 0.58 to 0.87. Although one item displayed a comparatively lower loading, all indicators exceeded commonly accepted thresholds and contributed meaningfully to the representation of perceived social support and relational experiences in digital contexts. Finally, the Digital Self-Regulation factor exhibited standardized loadings between 0.73 and 0.83, indicating a strong and coherent measurement of individuals' ability to manage time, attention, and boundaries in their digital technology use. Across all factors, the magnitude of the standardized loadings and their narrow confidence intervals demonstrate that the measurement model is stable and that the items reliably represent their intended constructs. These findings provide strong support for the construct validity of the four-factor Digital Well-Being Scale.

4.3. Measurement invariance across gender

To examine whether the scale functioned equivalently across gender groups, a multi-group confirmatory factor analysis (MG-CFA) was conducted. Although the Diagonally Weighted Least Squares (DWLS) estimator was preferred in the single-group CFA due to the ordinal nature of the data and violations of multivariate normality, the Maximum Likelihood (ML) estimator was used in the measurement invariance analyses. This decision was based on the large sample size and the comparative nature of invariance testing, where nested model comparisons and chi-square difference tests are central. Previous methodological research has shown that ML-based chi-square difference testing, particularly with robust corrections, provides stable and interpretable results in large samples even under non-normal data conditions (Cheung & Rensvold, 2002; Pavlov et al., 2020). Configural and metric invariance models were tested comparatively.

The configural invariance model, in which no equality constraints were imposed, showed a good fit to the data ($\chi^2 = 348.43$, $df = 256$, $CFI = 0.95$, $TLI = 0.94$, $RMSEA = 0.05$, $SRMR = 0.06$). This indicates that the same factor structure is valid for both gender groups. When factor loadings were constrained equal across genders (metric invariance), the model fit remained acceptable ($\chi^2 = 373.00$, $df = 271$, $CFI = 0.94$, $TLI = 0.93$, $RMSEA = 0.05$, $SRMR = 0.07$). The chi-square difference between the metric and configural models was not significant ($\Delta\chi^2 = 24.57$, $\Delta df = 15$, $p = 0.056$), and the change in CFI ($\Delta CFI = -0.01$) was below the 0.01 threshold. Thus, metric invariance was supported. Further constraining item intercepts to equality (scalar invariance) did not significantly worsen model fit ($\Delta\chi^2 = 20.78$, $\Delta df = 14$, $p = 0.107$; $\Delta CFI = 0.00$). Therefore, scalar invariance was also established. Collectively, these results demonstrate that the scale exhibits configural, metric, and scalar invariance across gender, indicating that the construct is measured equivalently for males and females in terms of structure, factor loadings, and intercepts. Therefore, it can be said that the measurement invariance is reasonably achieved (Cheung & Rensvold, 2002). These findings indicate that the scale operates equivalently in terms of structure, loading, and error variances across gender groups, thus enabling fair comparisons.

To enhance the psychometric rigor of the measurement model, composite reliability (CR), Average Variance Extracted (AVE), and discriminant validity indices were evaluated following the confirmatory factor analysis. The four latent factors demonstrated satisfactory internal consistency, with CR coefficients ranging from 0.70 to 0.82. The AVE values were 0.43 for F1, 0.44 for F2, 0.41 for F3, and 0.44 for F4. According to Fornell and Larcker (1981), AVE values of 0.50 or higher indicate adequate convergent validity. However, when AVE is below 0.50 but CR exceeds 0.60, convergent validity may still be considered acceptable. Discriminant validity was examined using the Fornell-Larcker criterion. The square roots of AVE (F1 = 0.65, F2 = 0.67, F3 = 0.64, F4 = 0.66) were consistently greater than the corresponding inter-factor correlations ($r = 0.19-0.63$), demonstrating that each latent variable is empirically distinct from the others. These values are presented in Table 5.

Table 5. Composite reliability, average variance extracted, and Fornell–Larcker discriminant validity indicators.

Factor	CR	AVE	F1	F2	F3	F4
F1	0.816	0.427	0.653	0.542	0.630	0.558
F2	0.797	0.444	0.542	0.666	0.352	0.334
F3	0.733	0.410	0.630	0.352	0.640	0.199
F4	0.700	0.439	0.558	0.334	0.199	0.662

Notes: CR: composite reliability; AVE: average variance extracted; $\sqrt{\text{AVE}}$: square root of AVE (diagonal). Bold values on the diagonal represent $\sqrt{\text{AVE}}$ for each latent construct, while off-diagonal entries represent inter-factor correlations. According to the Fornell–Larcker criterion, discriminant validity is established when a factor's $\sqrt{\text{AVE}}$ exceeds its correlations with other factors.

5. Reliability

The internal consistency of the developed Digital Well-Being Scale was evaluated in a multifaceted way on different samples (EFA, CFA, and criterion validity participants groups).

5.1. Exploratory factor analysis (EFA) participant group

The analyses conducted by the EFA group revealed that the scale has a high level of internal consistency. The reliability coefficients obtained for the entire scale are as follows: Cronbach's $\alpha = 0.874$. These values indicate that the scale has a highly reliable structure. Alpha values above 0.70 are considered acceptable, above 0.80 are good, and above 0.90 are excellent reliability levels (Hair et al., 2014).

The internal consistency coefficients for the subscales are as follows:

1. Subscale (Meaningful and Purposeful Digital Participation, 6 items): $\alpha = 0.833$
2. Subscale (Digital Security and Awareness, 5 items): $\alpha = 0.835$
3. Subscale (Digital Social Support and Relationships, 4 items): $\alpha = 0.765$
4. Subscale (Digital Self-Regulation, 3 items): $\alpha = 0.738$

All subscales demonstrate acceptable levels of internal consistency and consistently reflect the structures being measured.

5.2. Confirmatory factor analysis (CFA) participant group

The analyses conducted in the CFA participant group also support the reliability of the scale. Values calculated for the entire scale:

Cronbach's $\alpha = 0.856$

Cronbach's α values obtained for each subscale:

1. Subscale (Meaningful and Purposeful Digital Participation): $\alpha = 0.814$
2. Subscale (Digital Security and Awareness): $\alpha = 0.791$
3. Subscale (Digital Social Support and Relationships): $\alpha = 0.726$
4. Subscale (Digital Self-Regulation): $\alpha = 0.698$

These values indicate a good level of reliability, especially in the first two subscales, and an acceptable level of reliability in the last two subscales.

5.2.1. Criterion-related validity participant group 1

The reliability coefficients of the scale in the third sample group were also found to be high. Cronbach's α coefficients according to subscales:

1. Subscale (Meaningful and Purposeful Digital Participation): $\alpha = 0.836$
2. Subscale (Digital Security and Awareness): $\alpha = 0.826$
3. Subscale (Digital Social Support and Relationships): $\alpha = 0.691$
4. Subscale (Digital Self-Regulation): $\alpha = 0.781$

The overall Cronbach's α value for the scale was calculated as 0.879. These findings indicate that the developed scale yields reliable and consistent results across different samples.

5.2.2. Criterion-related validity participant group 2

The reliability coefficients of the scale in the fourth sample group were also found to be high. Cronbach's α coefficients according to subscales:

1. Subscale (Meaningful and Purposeful Digital Participation): $\alpha = 0.841$
2. Subscale (Digital Security and Awareness): $\alpha = 0.802$
3. Subscale (Digital Social Support and Relationships): $\alpha = 0.824$
4. Subscale (Digital Self-Regulation): $\alpha = 0.796$

The overall Cronbach's α value for the scale was calculated as 0.884. These findings indicate that the developed scale yields reliable and consistent results across different samples.

5.3. Criterion-related validity

As a result of criterion-based validity, significant and positive correlations were found between the developed *Digital Well-being Scale* and its subdimensions and the *General Well-being Scale (GWSSF)*. In particular, the Meaningful and Purposeful Digital Participation subscale showed a moderate correlation with the GWSSF ($r = 0.495$), the Digital Self-Regulation subscale showed a correlation of $r = 0.408$, the Digital Social Support and Relationships subscale showed a correlation of $r = 0.467$, and the Digital Security and Awareness subscale showed a correlation of $r = 0.398$ (all $p < 0.001$). Additionally, a strong and significant correlation was observed between the total score of the Digital Well-being Scale and the total score of the GWSSF ($r = 0.599$, $p < 0.001$). These findings indicate that the developed scale possesses adequate criterion-related validity.

Pearson correlation analyses revealed that *Digital Stress* was significantly and negatively correlated with the *Digital Well-being Scale*. Specifically, digital stress showed a weak to moderate negative correlation with Meaningful and Purposeful Digital Participation ($r = -0.232$, $p < 0.001$), Digital Security and Awareness ($r = -0.345$, $p < 0.001$), and Digital Self-Regulation ($r = -0.245$, $p < 0.001$). Moreover, the correlation between digital stress and the total score of the Digital Well-being Scale was also negative and significant ($r = -0.272$, $p < 0.001$). There was no significant correlation between digital stress and Digital Social Support and Relationships ($r = -0.023$, $p = 0.705$).

Pearson correlation analyses indicated that *digital literacy* was positively and significantly correlated with all subdimensions of the *Digital Well-being Scale*. Specifically, digital literacy was moderately correlated with Meaningful and Purposeful Digital Participation ($r = 0.439$, $p < 0.001$), Digital Security and Awareness ($r = 0.343$, $p < 0.001$), Digital Social Support and Relationships ($r = 0.234$, $p < 0.001$), and Digital Self-Regulation ($r = 0.521$, $p < 0.001$). Moreover, digital literacy was positively correlated with the total score of the Digital Well-being Scale ($r = 0.520$, $p < 0.001$).

After examining the correlations among the study variables, a multiple linear regression analysis was carried out. Prior to interpreting the model, all required regression assumptions were reviewed. The Durbin-Watson coefficient was 1.93, which indicates that the residuals did not display autocorrelation. Multicollinearity was also evaluated and found not to be problematic, as evidenced by the low VIF values (approximately 1.06) and high tolerance levels (0.945). The Condition Index values ranged between 1.00 and 18.10; none approached the commonly accepted threshold of concern, and the distribution of variance proportions suggested no clustering indicative of multicollinearity. Examination of the standardized residuals (-2.76 to 2.75) revealed no extreme values or indications of a deviation from normality. Moreover, the residuals did not exhibit a pattern consistent with heteroscedasticity, implying that the assumption of constant error variance was satisfied.

The regression analysis assessing whether digital well-being could be predicted by digital stress and digital literacy yielded a statistically significant model, $F_{(2, 281)} = 58.59$, $p < 0.001$. Altogether, the predictors accounted for 29% of the variance in digital well-being ($R^2 = 0.29$, Adjusted $R^2 = 0.29$). Digital literacy emerged as the most influential predictor ($\beta = 0.48$, $p < 0.001$), demonstrating that individuals

with higher levels of digital literacy reported higher levels of digital well-being. Digital stress also contributed meaningfully to the model, although to a lesser extent, showing a negative association with digital well-being ($\beta = -0.16$, $p = 0.002$).

6. Discussion

This study aimed to develop and validate a multidimensional measure of digital well-being grounded in contemporary psychological and human–computer interaction frameworks. The final 18-item structure includes four interrelated dimensions: Meaningful and Purposeful Digital Participation, Digital Self-Regulation, Digital Social Support and Relationships, and Digital Security and Awareness. Together, these dimensions capture both the protective and growth-oriented sides of individuals' experiences in digital settings. Compared with earlier instruments that emphasized hedonic satisfaction, emotional balance, or safe technology use (Gui et al., 2017; Kennedy & Baker, 2016), the present scale offers a more comprehensive approach. It highlights positive digital capacities—such as self-regulation, purpose, and social connection—that enable users to thrive online. In this way, the scale complements existing tools and advances the field by integrating risk-reduction and positive-development perspectives within a single measure.

The construct builds on established theories such as Self-Determination Theory (Deci & Ryan, 1985, 2000) and the PERMA model of well-being (Seligman, 2011), extending them to digital contexts. The PERMA framework offers a powerful lens for interpreting how flourishing occurs in digital environments. Meaningful participation reflects both engagement and meaning; digital social support aligns with the relational component; self-regulation corresponds to accomplishment through intentional use; and digital security contributes to emotional stability. Similarly, Self-Determination Theory clarifies how design environments support or frustrate autonomy, competence, and relatedness. Autonomy is shaped by interface transparency and control, competence by users' ability to manage cognitive demands and navigate risks, and relatedness by meaningful online interactions. By positioning the four dimensions of the scale within these two well-established psychological models, the findings demonstrate that digital well-being emerges from the fulfillment of basic psychological needs in technologically mediated contexts. This integrated perspective also provides a conceptual foundation for HCI research by highlighting how design decisions can enhance or undermine these pathways to flourishing.

The results of the criterion-related validity analyses provide robust evidence for the concurrent validity of the developed Digital Well-being Scale. The significant and positive correlations between the scale and the General Well-being Scale indicate that digital well-being reflects broader psychological well-being processes. In particular, the moderate associations observed between meaningful digital participation, digital self-regulation, social connectedness, and digital security with general well-being suggest that individuals who engage purposefully and regulate their technology use experience greater overall well-being. Consistent with theoretical expectations, digital stress was found to be negatively associated with digital well-being and its key components, indicating that higher levels of digital strain correspond to lower levels of purposeful digital engagement, self-regulation, and perceived security. Interestingly, the absence of a significant relationship between digital stress and digital social support implies that social connections in digital contexts may remain relatively unaffected by stress experiences. Furthermore, the positive associations between digital literacy and all dimensions of digital well-being highlight the essential role of digital competencies in fostering adaptive and healthy engagement with technology. Individuals with stronger digital literacy skills appear more capable of managing online risks, maintaining meaningful digital participation, and exercising self-control in digital environments. Together, these findings support the construct validity of the Digital Well-being Scale and underscore the multidimensional interplay between literacy, stress, and well-being in digital contexts.

Beyond its psychological grounding, the scale contributes meaningfully to HCI by offering a structured way to evaluate how design decisions influence user well-being. Each dimension corresponds to central HCI concerns: meaningful participation reflects user agency and value-driven engagement; self-regulation relates to cognitive load and the impact of persuasive or attention-demanding interfaces; social support aligns with socio-technical affordances; and digital security corresponds to privacy, trust, and risk communication. By linking these dimensions to measurable outcomes, the scale provides an

empirical basis for examining how interface elements, algorithmic architectures, and interaction patterns shape users' cognitive and emotional states.

This theoretical positioning advances HCI by framing digital well-being as a dynamic process emerging from the interaction between system design, user competencies, and psychological needs. The scale can be used to assess the well-being implications of design interventions, compare interface alternatives, evaluate algorithmic transparency efforts, or examine how notification and content-delivery systems influence user autonomy and attentional balance. As such, it offers a foundation for integrating well-being-centered principles into user experience research and design practice.

Overall, the findings support a coherent and theoretically grounded model of digital well-being with strong relevance for psychological theory and HCI scholarship. The instrument enables a more nuanced understanding of how digital environments contribute to or detract from human flourishing and provides a practical tool for future research aiming to create healthier, more balanced, and autonomy-supportive digital ecosystems.

6.1. Limitations and future directions

Although this study provides a psychometrically sound tool for assessing digital well-being, it has some limitations. First, the sample consists only of young adults, the majority of whom are university students. In addition, the sample predominantly represents individuals from a middle socioeconomic background. This may limit the generalizability of the findings to different age groups, socioeconomic levels and levels of digital experience. Accordingly, the findings may not fully generalize to children, older adults, or individuals from more diverse socioeconomic and cultural backgrounds. In future studies, it is recommended to include children, older adults and groups that may have limited access to digital technologies. Expanding the demographic diversity of the sample may improve the external validity of the scale.

Secondly, the data were collected through self-report method. This type of data is susceptible to social desirability bias and may not accurately reflect participants' actual digital behaviors. Such biases may influence participants' responses regarding their digital well-being, digital stress, and digital literacy levels. The use of objective measures such as screen time logs, app usage data, or behavioral observations is recommended for future research. Combining self-report data with objective digital behavior indicators may provide a more robust and reliable assessment of digital well-being.

Third, the study is based on a cross-sectional design. Therefore, inferences regarding the change in digital well-being over time or its causal effects cannot be made. In particular, causal relationships between digital well-being, digital literacy, and digital stress cannot be established. The sustainability and developmental processes of digital well-being should be examined through longitudinal designs. Longitudinal research would allow researchers to examine how digital well-being evolves over time and whether digital literacy or digital stress predicts long-term well-being outcomes.

In addition, the content validity stage involved five experts from relevant disciplines. Their diverse expertise contributed to the conceptual clarity of the items, yet a larger panel could have provided broader feedback and increased representativeness.

Finally, although the present study contributes to the digital well-being literature by developing a theoretically grounded and psychometrically robust measurement tool, its contribution can be considered incremental within an emerging field. The instrument extends existing frameworks but does not radically redefine the construct. Moreover, as the validation process was conducted within a single cultural context and mainly with young adult participants, the generalizability of the findings is limited. Digital well-being may be influenced by cultural norms, values, and patterns of technology use, which may differ across societies. Future research should aim to conduct cross-cultural validation and include more diverse samples (eg, different age groups, occupational backgrounds, and cultural settings) to enhance the universality and applicability of the scale. Such cross-cultural studies would help determine whether the scale demonstrates measurement equivalence across different cultural contexts.

6.2. Implications

The findings of this study contribute to a more nuanced understanding of digital well-being by introducing a multidimensional and theoretically grounded scale. The instrument allows researchers and practitioners to examine both the constructive and protective sides of digital engagement, offering insight into how individuals sustain balance, meaning, and positive functioning in digital environments. Thus, the scale provides a measurable framework for HCI research on topics such as social interaction, user autonomy, security, and privacy.

Beyond research settings, the scale can serve as a practical tool for educators, counselors, and policy-makers seeking to design programs that promote healthier and more purposeful digital use. Future work could apply the scale across diverse populations and cultural contexts to test its broader applicability and to explore how digital well-being develops as technology use patterns evolve.

7. Conclusion

This study presents a valid and reliable instrument that assesses the digital well-being of individuals. The scale reveals that digital experiences are related not only to duration of use but also to psychosocial dimensions such as mindfulness, self-regulation, social relationships and emotional balance. The four-factor structure has a strong theoretical and statistical basis. The scale has demonstrated high validity and reliability in young adult samples. For researchers, mental health professionals, educators, and policy makers, this scale provides a functional tool for qualitatively assessing digital behaviors, identifying risky patterns of use, and developing intervention programs. In future research, testing the scale in different cultural contexts, age groups and digital platforms will contribute to a more holistic understanding of the concept of digital well-being.

Ethical approval

This study was conducted in accordance with established ethical standards. All necessary approvals and permissions were obtained prior to the conduct of the research, and the privacy, confidentiality, and rights of the participants were fully protected. Informed consent was obtained from all participants involved in the study. Ethical approval for this research was granted by the Trakya University Social and Human Sciences Ethics Committee (Approval No: 13.05.2025-843522).

Author contributions

All aspects of the study, including conceptualization, methodology, data curation, formal analysis, investigation, validation, visualization, and writing (original draft and review & editing), were carried out by Tuğba Türk Kurtça.

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Data availability statement

The data supporting the findings of this study are available from the author upon reasonable request.

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