

International Journal of Human–Computer Interaction

ISSN: 1044-7318 (Print) 1532-7590 (Online) Journal homepage: www.tandfonline.com/journals/hihc20

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To cite this article: Anna Enrica Tosti, Anastasiia Shyroka, Anastasiia Chorna, Andrea Guazzini & Mirko Duradoni (02 Mar 2026): Understanding Digital Well-Being: Validation of the Digital Life Balance Scale in the Ukrainian Population, International Journal of Human–Computer Interaction, DOI: 10.1080/10447318.2026.2633205

To link to this article: https://doi.org/10.1080/10447318.2026.2633205

Published online: 02 Mar 2026.

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INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
https://doi.org/10.1080/10447318.2026.2633205

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Understanding Digital Well-Being: Validation of the Digital Life Balance Scale in the Ukrainian Population

Anna Enrica Tosti[a,b], Anastasiia Shyroka[c], Anastasiia Chorna[c], Andrea Guazzini[b] and Mirko Duradoni[d]

[a]Department of Statistics, Computer Science, Applications, University of Florence, Florence, Italy; [b]Department of Education, Literatures, Intercultural Studies, Languages and Psychology, University of Florence, Florence, Italy; [c]Department of Psychology and Psychotherapy, Ukrainian Catholic University, Lviv, Ukraine; [d]Department of Human and Social Sciences, Mercatorum University, Rome, Italy

ABSTRACT

The integration of digital technologies into daily life has raised concerns about the psychological effects of unbalanced use. Digital Life Balance (DLB) refers to the perceived harmony between online engagement and offline experiences. This study validated the Ukrainian version of the DLB scale in a sample of 350 participants (76.9% females). Participants completed the DLB alongside measures of anxiety, psychological flexibility, affect, life satisfaction, smartphone addiction, social media engagement, and bedtime procrastination. Confirmatory factor analysis supported a one-dimensional structure, with satisfactory internal consistency ($\omega = 0.87$). Measurement invariance was established across gender (configural, metric, scalar, and strict), while scalar invariance was not supported across age groups. DLB showed positive correlations with life satisfaction and positive affect, and negative correlations with anxiety, psychological inflexibility, negative affect, bedtime procrastination, smartphone addiction, and social media engagement. Individuals with clinically relevant anxiety reported significantly lower DLB. The Ukrainian DLB demonstrates good reliability and validity for research and clinical applications.

KEYWORDS

Digital life balance; information and communication technology; psychological well-being; scale validation; Ukraine

1. Introduction

In recent decades, thanks to the widespread availability of new media devices and the increased accessibility of the Internet, there has been a rapid adoption of Information and Communication Technologies (ICT; Shepherd, 2004). This digital revolution has progressively changed the modern lifestyle, with ICT now deeply embedded in every aspect of daily life, including healthcare, education, work environments, entertainment, relationships, and communication (Cunningham & Craig, 2016; Jafari et al., 2020; Jeilani & Hussein, 2025; Parteka et al., 2024; Wang et al., 2024). Globally, more than two-thirds of the world's population uses the internet, and in Ukraine approximately 82.4% of the population (31.5 million individuals) were online at the beginning of 2025, rising to about 89.6% (35.3 million individuals) by the end of 2025 according to recent DataReportal (2025a, 2025b, 2026) digital reports. Since the full-scale invasion in 2022, ICTs have become essential tools for resistance and resilience, enabling communication, distance learning, air raid alerts, resource mobilization, real-time information sharing, and connection with displaced loved ones (Guidi et al., 2025; Londar & Pietsch, 2023; Zarembo et al., 2025; Ye et al., 2023). Ukrainians increasingly rely on mobile applications and chatbots for psychological self-help, further intensifying smartphone use (Frankova & Sijbrandij, 2025). However, heightened exposure to war-related content and information overload via ICTs can exacerbate stress and psychological distress (Li et al., 2024). As war-related activities move online and integrate into daily life, distinguishing between healthy and dysfunctional ICT use has become increasingly urgent.

CONTACT Mirko Duradoni mirko.duradoni@unimercatorum.it Department of Human and Social Sciences, Mercatorum University, Piazza Mattei 10, 00186, Rome, Italy

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In today's digital age, the inappropriate use of ICT is a growing concern, largely due to the constant accessibility of the internet (Vorderer et al., 2016). While these technologies undoubtedly have the potential to connect people, they may also contribute to a growing sense of disconnection and fragmented attention (Turkle, 2011). Indeed, if misused, ICT can disrupt the balance between virtual and real life. This can lead to dysfunctional usage patterns and have a negative impact on well-being (Dadi et al., 2024; Kim & Davis, 2009).

The psychology of Harmony and Harmonization (Di Fabio & Tsuda, 2018) offers a valuable insight for understanding when the reliance on ICT may not be optimal. Inspired by traditional Eastern philosophies as well as Western perspectives, this framework draws on both to conceptualize harmony as a dynamic and adaptive process that integrates diverse elements into a balanced and cohesive whole. Thus, achieving and maintaining this balance is not a static endpoint, but rather requires continuous adjustment and rebalancing in response to the evolving circumstances and environments one faces. In this context, the notion of "Digital Life Balance" (DLB) has been introduced as a construct aimed at exploring the perceived equilibrium between how individuals manage their digital and real-life lives (Duradoni et al., 2022). DLB can therefore be understood as a specific manifestation of psychological harmony in the digital era, reflecting individuals' capacity to regulate, integrate, and rebalance digital and offline domains in a way that supports overall functioning and well-being.

DLB has been positively associated with life satisfaction in previous studies (Duradoni et al., 2022). Indeed, a higher level of DLB indicates the positive integration between one's online and offline activities, supporting well-being. Notably, today's hyper-connected society can become an escape for individuals who turn to digital technologies to compensate for unmet needs in their offline lives. The immediacy of the internet and the constant availability of feedback, anytime and anywhere, can serve as a convenient, albeit often temporary, source of instant gratification (Alenezi et al., 2023; Omar & Subramanian, 2013). While this may provide short-term relief, over-reliance on the technologically mediated world can intensify the imbalance between virtual and real-life experiences, potentially negatively affecting well-being (Duradoni et al., 2022; Lima-Costa et al., 2024). Conversely, DLB has shown a negative association with maladaptive outcomes such as anxiety (Duradoni et al., 2024a), which is been linked to the use of digital technologies as a coping mechanism during periods of hardship (Elhai et al., 2016; McNicol & Thorsteinsson, 2017).

A major contributor to this misalignment is the design of modern digital platforms and software, which are deliberately created to encourage prolonged user engagement. Features such as gamification, tailored recommendations, notifications, and alerts are specifically designed to capture and maintain users' attention for extended periods (Weinstein & Lejoyeux, 2010). E-commerce platforms, online games, and social media are crafted with strategies in mind that promote habitual and sometimes compulsive consumption. This can lead to problematic internet use, such as excessive smartphone screen time and unhealthy patterns of social media engagement, thereby shifting the balance toward greater ICT use with potential adverse consequences for overall well-being (Duradoni et al., 2022). Previous research has shown that higher levels of DLB are inversely associated with digital addiction and over-reliance on social media interactions (Duradoni et al., 2024b), suggesting that DLB reflects individuals' ability to withstand or counteract engagement-driven digital environments. Moreover, social media engagement, characterized by frequent and prolonged use, may reflect an overuse of technology that interferes with daily functioning and interpersonal relationships. An example of this is phubbing (i.e., the act of ignoring those physically present to engage with one's smartphone instead; Chotpitayasunondh & Douglas, 2016; Guazzini et al., 2021). High levels of social media engagement have also been associated with an increased risk of social media addiction, anxiety, and loneliness (Duradoni et al., 2024b), suggesting that excessive digital use can significantly undermine a balanced and healthy relationship with ICT.

A consequence of difficulty in balancing ICT use is bedtime procrastination (i.e., the voluntary delay of going to bed without a justifiable reason; Kroese et al., 2016), reflecting an inability to appropriately regulate daily life in favor of digital behaviors. Individuals with high levels of bedtime procrastination are more likely to spend time in stimulating activities before sleep, such as browsing the internet, watching videos, or using social media (Chung et al., 2020). These behaviors have been linked to negative outcomes for well-being, including poorer sleep quality and disruptions in life balance, such as

increased daytime sleepiness and fatigue (Herzog-Krzywoszanska et al., 2024). Indeed, maintaining balance requires a combination of consistency and flexibility. Consistency provides the basis for stable routines and healthy habits, while flexibility enables us to make necessary adjustments in response to the demands of everyday life (Besika et al., 2021). In the context of DLB, cognitive flexibility allows individuals to dynamically regulate ICT use across changing situational demands, priorities, and emotional states, preventing both rigid over-control and unregulated overuse.

This perspective highlights the importance of having a reliable and valid tool to assess individuals' perceptions of their ability to integrate ICT into their lives while using it in a balanced way. Building on the original Italian version of the DLB scale (Duradoni et al., 2022), and following its adaptations in Brazil, Turkey, and Russia (Lima-Costa et al., 2024; Soysal et al., 2024; Tosti et al., 2026), this study intended to develop the Ukrainian version of the scale. In addition to providing the Ukrainian adaptation, this study makes several novel contributions. This study is the first validation to examine measurement invariance not only across gender but also across age groups, providing insight into how the construct of digital life balance may function distinctly across different life stages. Moreover, for the first time, it examined the relationship between digital life balance and a comprehensive new set of psychological variables, including psychological inflexibility and bedtime procrastination. Lastly, it is the first study to show an association between the severity of anxiety on several levels and the DLB scores, highlighting its potential utility for the early identification of digital imbalance as a correlate of mental health symptoms. Taken together, these contributions mark an important advancement in the cross-cultural applicability of the DLB scale.

1.1. Aim of the study and hypotheses development

This study aimed to validate and assess the reliability of the DLB scale translated into Ukrainian. To achieve this, measures of anxiety, psychological flexibility, emotional experiences, smartphone addiction, social media engagement, and bedtime procrastination were included to better understand the construct and its relationships with related psychological variables.

In addition, this study aimed to examine the measurement invariance of the scale across gender and age groups to ensure its applicability and relevance across these socio-demographic categories. This will help to determine whether the DLB operates similarly and produces comparable results across different populations, thereby supporting its wider utility in different contexts.

2. Method

2.1. Recruitment and participants

Participants were recruited through convenience sampling using several strategies to achieve diversity and representativeness. Firstly, research information was shared using social media and online groups (stories and posts on Instagram and in various Facebook groups), allowing any individual who saw the announcement and wished to participate to access the anonymous Google Forms survey via a public link. The Google Form header described the study's purpose (questionnaire adaptation and validation), procedures, voluntary participation, the right to withdraw at any time, and provided the researcher's contact email. Participants provided informed consent electronically. Before starting the questionnaire, they read an information sheet explaining the study's purpose, procedures, voluntary participation, confidentiality, and the right to withdraw. Proceeding with the survey indicated their consent. No identifying data were collected. Also, colleagues from universities from different parts of Ukraine were invited to share the information with their friends and students. Inclusion criteria required participants to be 18 years or older, residents or citizens of Ukraine, and able to read Ukrainian; no exclusion criteria were applied. The study received approval from the Institutional Ethical Review Board of the Ukrainian Catholic University, Protocol № 68/24-n/e.

The final sample (Table 1) consisted of 350 people, including 269 females (76.9%), 77 males (22%), and 4 participants (1.1%) who either preferred not to disclose their gender or did not identify with any of the above options. The sample was predominantly composed of people between the ages of 18 and

25, with 215 participants in this age group. There were also 35 participants between the ages of 26 and 35, followed by 49 participants between the ages of 36 and 45. The next age group, between 46 and 55, had 37 participants, and finally, 14 participants were aged 55 or older.

2.2. Measures

2.2.1. Sociodemographic

All participants were asked to provide information on their socio-demographic characteristics, such as their age and gender.

2.2.2. Digital life balance scale (DLB, Duradoni et al., 2022)

The scale consists of four items, each scored on a 7-point Likert scale ranging from 1, indicating the lowest level of agreement ("strongly disagree"), to 7, indicating the highest level of agreement ("strongly agree"). A higher total score indicates a greater sense of life balance.

With the authorization from the original authors, the scale was translated from Italian to Ukrainian using a forward and back-translation approach (Beaton et al., 2000). Three psychologists (including the authors of the study) who had prior experience in adapting questionnaires and who were fluent in both Ukrainian and English took part in the process. Two of them independently translated the questionnaire into Ukrainian. Afterward, the third psychologist carried out the backward translation of both versions. They then agreed on the most appropriate final translation. During the backward translation procedure, the focus was on ensuring that the original meaning of the statements was preserved while making sure the wording sounded as natural as possible in Ukrainian. A pilot pre-testing stage was conducted with 25 psychology students to gather feedback specifically aimed at evaluating item clarity, comprehensibility, semantic equivalence, and cultural relevance. Participants were asked to identify unclear wording, ambiguous expressions, or culturally inappropriate formulations. This feedback was used to refine item wording and improve clarity and cultural suitability, ensuring that the final items were unambiguous and easily understood by the target population (see Table A1 in the Appendix A).

2.2.3. General anxiety disorder 7 (GAD-7; Spitzer et al., 2006)

The Ukrainian version of the seven-item self-screening tool designed to assess the severity of generalized anxiety symptoms scale was used (Aleksina et al., 2024). Respondents rate the frequency of anxiety symptoms experienced over the past two weeks using a 4-point Likert scale ranging from 0 (not at all) to 3 (almost every day). Higher scores indicate a greater presence of anxiety symptoms, categorized as follows: 0–4 (minimal anxiety), 5–9 (mild anxiety), 10–14 (moderate anxiety), and 15–21 (severe anxiety). In the current sample, the scale showed high internal consistency ($\omega = 0.88$).

2.2.4. Acceptance and action questionnaire-II (AAQ-II; Bond *et al.*, 2011)

This scale consists of seven items designed to assess psychological inflexibility. Responses are measured on a 7-point Likert scale ranging from 1 (never true) to 7 (always true), with higher scores indicating greater levels of psychological inflexibility. The Ukrainian version of the AAQ-II, as translated by Shyroka and Mykolaychuk (2021), was used in this study. The scale has excellent reliability, with a ω coefficient of 0.91.

2.2.5. The positive and negative affect schedule (PANAS; watson, clark, & tellegen, 1988)

PANAS is a 20-item instrument divided into 10 items assessing positive emotions and 10 items assessing negative emotions experienced in the past week. Responses are given on a 5-point Likert scale ranging from "very little or not at all" to "a great deal". Higher scores on each scale indicate greater levels of affect. This study employed the Ukrainian version of the PANAS translated by Klimanska and Haletska (2020). The scale has strong internal consistency, with a reliability ω coefficient of 0.88.

2.2.6. Satisfaction with life scale (SWLS, Diener et al., 1985)

SWLS measures individuals' overall life satisfaction through five items that reflect their assessment of their life. Participants respond to each statement using a 7-point Likert scale, where 1 indicates strong

Table 1. Socio-demographic information of the sample.

	n	Percentage (%)
Gender		
Male	77	22
Female	269	76.9
Other	4	1.1
Age		
18–25	215	61.4
26–35	35	10
36–45	49	14
46–55	37	10.6
55+	14	4

disagreement and 7 indicates strong agreement. Higher total scores, which can range from 5 to 35, indicate greater life satisfaction. The Ukrainian translation of the SWLS by Olefir and Bosniuk (2024) was used. In this research, the scale showed a high reliability of $\omega = 0.82$.

2.2.7. Smartphone addiction scale (SAS; Kwon et al., 2013)

SAS is designed to evaluate the potential risk for smartphone addiction. In this study, only the Daily-Life Disturbance Subscale was used. This instrument consists of 5 items that respondents rate using a six-point Likert scale, ranging from 1 (never) to 6 (always). A higher total score indicates a greater risk of dysfunctional smartphone usage. Only the Daily-Life Disturbance Subscale of the SAS was used because it aligns most closely with the aim of the study—assessing the convergent validity of the Digital Life Balance questionnaire. This subscale specifically captures the aspects of digital use that interfere with everyday functioning, which is conceptually relevant to the construct measured by the DLB. Additionally, selecting only this subscale helped reduce the overall number of items participants were required to complete, thereby minimizing respondent burden. The version used in this study was the Ukrainian translation of the SAS by Bilyk (2021).

The reliability of the scale is supported by a McDonald's ω of 0.82.

2.2.8. Social media engagement questionnaire (SME-Q; Przybylski et al., 2013)

The scale consists of five items that assess participants' use and engagement with social media throughout the day, from morning until bedtime, in the past week. Responses are recorded on an 8-point Likert scale, ranging from 0 (not on any day last week) to 7 (every day last week), with higher scores indicating greater social media engagement. The scale was translated into Ukrainian and showed good reliability in the current sample ($\omega = 0.86$).

2.2.9. Bedtime procrastination scale (BPS; Kroese et al, 2014)

The BPS is a self-report measure that assesses the tendency to procrastinate bedtime. It consists of nine items scored on a scale from 1 ("almost never") to 5 ("almost always"), with higher scores indicating a greater tendency to delay bedtime. The Ukrainian version used was translated by Dudnyk (2023). In this study, the scale showed high internal consistency, with a McDonald's ω of 0.89.

2.3. Data analysis

The data were analyzed with IBM SPSS software (Version 27), SPSS Amos (Version 24), and RStudio (RStudio Team, 2020). During the analysis process, the scoring for each instrument was first computed according to the standardized methods established in the literature. Following the calculation of the descriptive statistics for the sample (i.e., age and gender), the next stage of the analysis involved computing the mean and standard deviation, as well as assessing the distribution of each item on the DLB Ukraine scale. Therefore, skewness and kurtosis were calculated. Given the sample size of over 300, a skewness value greater than 2 or a kurtosis value greater than 7 was considered an indicator of substantial non-normality (Kim, 2013).

Later, Confirmatory Factor Analysis (CFA; Brown, 2015; Jöreskog, 1969) was used to assess the one-dimensional model proposed by the original scale (Duradoni et al., 2022). Model fit was assessed using

absolute fit indices, including chi-squared to degrees of freedom (χ^2/df; Jöreskog, 1969), Root Mean Square Error of Approximation (RMSEA; Steiger, 1990), and Standardized Root Mean Squared Residual (SRMR; Bentler, 1995). These indices provide insight into the agreement of parameter estimates with the true parameters of the population, and according to established guidelines, values of $\chi^2/df \leq 3$, RMSEA $\leq$ 0.06, and SRMR $\leq$ 0.08 are considered indicative of good fit (Hu & Bentler, 1999). In addition, incremental fit indices such as the Comparative Fit Index (CFI; Bentler, 1990) and the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973) were used. For both indices, values of 0.90 or greater are interpreted as indicating a good model fit (Bentler & Bonett, 1980).

Convergent validity of the measurement model was further evaluated using the Average Variance Extracted (AVE), while internal consistency reliability was assessed using Composite Reliability (CR). AVE values of 0.50 or greater were considered indicative of adequate convergent validity, and CR values of 0.70 or higher were interpreted as evidence of acceptable construct reliability (Fornell & Larcker, 1981; Hair et al., 2006).

The appropriate sample size for the CFA analysis followed the standard recommendation of a 10:1 respondent-item ratio (Comrey, 1988), which in the case of a four-item scale would require a minimum of 40 participants. The final sample of 350 participants exceeded this threshold, providing more than adequate power for the CFA and all subsequent analyses.

The internal consistency of the DLB scale was assessed using McDonald's Omega. Values of 0.90 are considered very good, 0.80 is considered good, and 0.70 is considered acceptable (Kline, 2015).

As both a Pearson correlation and an ANOVA were planned, a priori sample size calculations were performed using power analysis for both statistical tests. The Pearson correlation coefficient was to be calculated between the DLB total score and the GAD-7, AAQ-II, PANAS, SWLS, SAS, SME-Q, and BPS scale total scores, while an ANOVA would assess the differences between the DLB and GAD − 7 resulting level of anxiety groups. Moreover, a Receiver Operating Characteristic (ROC) analysis was performed to explore the discriminative capacity of DLB scores in identifying individuals with relevant anxiety symptoms (GAD − 7 score of $>=$10).

The required minimum sample size was determined based on the analysis requiring the largest number of observations. For the Pearson correlation, a sample size of 153 was considered sufficient to achieve a statistical power of 0.80 at a significance level of 0.05, allowing the detection of a small to medium effect size ($r = 0.20$, Cohen, 2013). The power analysis indicated a minimum sample size of 280 to achieve 80% power to detect a small-medium effect size for the ANOVA test with a significance criterion of $\alpha = 0.05$ ($f^2 = 0.20$, Cohen, 2013). A final sample of 350 participants was therefore considered adequate for hypothesis testing.

Finally, measurement invariance across gender (i.e., females and males) and age groups (i.e., younger individuals under 25 years and older individuals over 25 years) was assessed using multi-group confirmatory factor analyses (MGCFA, Brown, 2006).

The analysis began with the assessment of configural invariance, allowing free estimation of all parameters for each group, which ensured that the factor structure was consistent across both gender and age groups. This step verified that the underlying model was the same for all groups and provided a basis for the following comparisons.

Next, to assess metric invariance, factor loadings were constrained to be equal across gender and age groups. This step tested whether the strength of the relationship between each observed item and the latent construct was equivalent across groups, ensuring that the construct had the same conceptual meaning for all participants.

Scalar invariance was also assessed this time by imposing equality constraints on the item intercepts across groups. Establishing scalar invariance allows for meaningful comparisons of latent means across gender and age groups by ensuring that any observed differences are not due to group-specific response biases.

Finally, residual invariance was examined by constraining the residual variances of the observed items to be equal across gender and age groups. This level of invariance tests whether the amount of unexplained variance associated with each item is consistent across groups, thereby assessing the equivalence of measurement reliability across subpopulations.

Table 2. Descriptive statistics of the DLB items.

Items	Mean	SD	Skewness	Kurtosis
DLB 1	4.13	1.61	−.004	−.732
DLB 2	4.02	1.85	−.082	−1.188
DLB 3	3.84	1.82	.208	−1.070
DLB 4	3.97	1.81	.159	−1.052

$N = 350$; *SD*: Standard Deviation.

Chi-squared difference tests ($\Delta\chi^2$) were used to assess whether increasingly restricted models (metric, intercept, and residual) significantly differed from their less restricted counterparts. Non-significant differences in model fit supported the invariance of the measurement structure across groups defined by gender and age. Moreover, given the sensitivity of the chi-square test to sample size, changes in the comparative fit index (ΔCFI) of less than 0.005 were used as criterion for evaluating measurement invariance (Chen, 2007).

3. Results

3.1. Descriptive statistics

Table 2 provides an overview of the descriptive statistics for each DLB item, with mean scores ranging from 3.84 to 4.13 and standard deviations ranging from 1.61 to 1.85. Further assessment of skewness and kurtosis revealed no major deviations from normality for any of the items.

3.2. Confirmatory factor analysis

The one-dimensional factor model, as originally proposed by the authors and in its subsequent adaptations in other languages (Duradoni et al., 2022; Lima-Costa et al., 2024; Soysal et al., 2024; Tosti et al., 2026) was tested using Maximum likelihood (ML) estimation. The indices demonstrated an excellent fit ($\chi^2(2) = 2.884$, $p = 0.236$, with a χ^2/df ratio of 1.42; $p = 0.24$; TLI = 0.99; CFI = 0.99; SRM$R = 0.01$; RMSEA = 0.04, 90% CI [0.000, 0.118], $p = 0.499$). Standardized factor loadings were all significantly different from zero, ranging from 0.58 to 0.90 (Figure 1), all exceeding the acceptable threshold of 0.50 (Hair et al., 2006).

3.3. Reliability

McDonald's ω coefficient was calculated to assess the internal consistency of the scale. The results indicated satisfactory reliability, with a McDonald's ω coefficient of 0.87 (95% CI [0.85, 0.89]). Moreover, the unidimensional model showed satisfactory convergent validity (AVE = 0.63) and high composite reliability (CR = 0.87). The contribution of each item to the overall scale score was assessed using item-total correlations. All items demonstrated moderate to strong correlations with the total score, ranging from 0.55 to 0.81, thereby supporting the internal consistency of the scale.

3.5. Invariance across gender and age

First, configural invariance for gender was tested ($\chi^2(4) = 6.23$, $p = 0.182$), indicating that the single-factor structure was shared by both genders (Table 3). The difference in fit between the configural and metric models ($\Delta\chi^2(3) = 0.520$, $p = 0.915$) was not significant and the change in CFI (ΔCFI = 002) supported metric invariance and suggesting that factor loadings were equal across groups. Scalar invariance was confirmed as the intercepts were invariant across males and females ($\Delta\chi^2(4) = 5.470$, $p = 0.242$) and change in CFI (ΔCFI = 001), ensuring that any group differences in means were not influenced by scale properties. Finally, evidence for strict measurement invariance was observed. The chi-square difference test was non-significant, $\Delta\chi^2(5) = 8.711$, $p = 0.121$, and the change in CFI met the recommended criterion (ΔCFI = 0.005), supporting the equivalence of residual variances across groups.

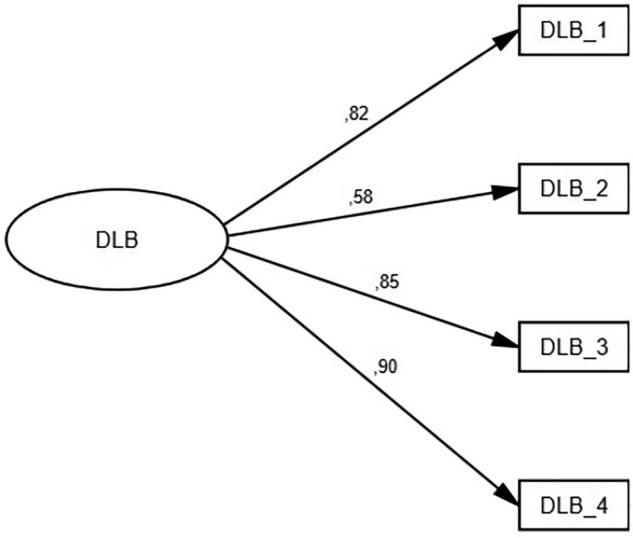


Figure 1. Results of confirmatory factor analysis of the DLB.

Table 3. Goodness-of-fit indices for invariance of the DLB across gender and age.

Model: Invariance level	$\chi^2(df)$	CFI	Model comparison	$\Delta\chi^2$	Δdf	p	ΔCFI
Gender							
Model 0: Configural (unconstrained)	6.233 (4)	.997	–	–	–	.182	–
Model 1: Metric (measurement weight)	6.752 (7)	.999	Model 1 vs Model 0	.520	3	.915	.002
Model 2: Scalar (measurement intercepts)	12.223 (11)	.998	Model 2 vs Model 1	5.470	4	.242	.001
Model 3: Strict (measurement error)	20.934 (16)	.993	Model 3 vs Model 2	8.711	5	.121	.005
Age							
Model 0: Configural (unconstrained)	7.787 (4)	.995	–	–	–	.100	–
Model 1: Metric (measurement weight)	9.061 (7)	.997	Model 1 vs Model 0	1.274	3	.735	.002
Model 2: Scalar (measurement intercepts)	22.580 (11)	.984	Model 2 vs Model 1	13.519	4	.009	.013
Model 3: Strict (measurement error)	26.183 (16)	.986	Model 3 vs Model 2	3.603	5	.608	.002

$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.
χ^2: Chi Square; *df*: degree of freedom; CFI: Comparative Fit Index; $\Delta\chi^2$: difference in Chi Square; Δdf: difference in degrees of freedom; ΔCFI: Difference between CFIs.

The age invariance analysis followed a similar procedure and a series of nested model comparisons were evaluated using χ^2 difference tests and change in CFI. The first step was to assess the configural model, which was not significant ($\chi^2(4) = 7.787$, $p = 0.100$). This result confirmed that the single-factor structure of the scale was also consistent across the two age groups. In a second step, metric invariance was assessed by comparing the configural and metric models. The change in χ^2 per degree of freedom ($\Delta\chi^2(3) = 1.274$, $p = 0.735$) was also not significant and CFI change was below the recommended cutoff (ΔCFI = 0.002, indicating that metric invariance was achieved and that the factor loadings did not differ between the age groups. Finally, scalar invariance was tested by comparing the metric and scalar models. The result ($\Delta\chi^2(4) = 13.519$, $p = 0.009$; ΔCFI = 0.013) did not support scalar invariance, indicating that the intercepts of the items are not equivalent between younger and older individuals.

3.6. External validity of the DLB scale

Table 4 presents the correlations between the Ukrainian version of the DLB and other observed variables. Positive significant correlations were found between DLB and SWLS ($r = 0.36$, $p < 0.001$) and PANAS+ ($r = 0.32$, $p < 0.001$). Significant negative correlations were also found between DLB and GAD − 7 ($r = -0.33$, $p < 0.001$), AAQ − 2 ($r = -0.40$, $p < 0.001$), PANAS- ($r = -0.31$, $p < 0.001$), SAS ($r = -0.48$, $p < 0.001$), SME-Q ($r = -0.27$, $p < 0.001$), and BPS ($r = -0.32$, $p < 0.01$).

External validity was also assessed using ANOVA analysis between the DLB total score and GAD − 7 scores divided into four anxiety severity groups (i.e., minimal, mild, moderate, and severe; Table 5). Levene's test for homogeneity of variance was performed first and showed a non-significant result ($p = 0.473$), indicating that the assumption of equal variances across groups was met. Furthermore, the Q-Q

Table 4. Means, standard deviations, and correlations between the DLB and other measures of well-being and technology addiction.

	M	SD	1.	2.	3.	4.	5.	6.	7.	8.
1. DLB	15.96	5.99								
2. GAD-7	8.18	4.66	−.33***							
3. AAQ-2	25.54	10.42	−.40***	.66***						
4. PANAS+	14.57	4.12	.32***	−.30***	−.40***					
5. PANAS−	12.88	4.30	−.31***	.75***	.62***	−.36***				
6. SWLS	20.14	6.197	.36***	−.31***	−.44***	.41***	−.30***			
7. SAS	13.58	5.297	−.48***	.37***	.43***	−.23***	.37***	−.13*		
8. SME-Q	20.81	10.84	−.27***	.20***	.27***	−.11*	.22***	−.12*	.40***	
9. BPS	25.90	7.727	−.32***	.29***	.33***	−.26***	.27***	−.13*	.45***	.30***

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.
M: Mean; *SD*: Standard Deviation; $N = 350$; DLB: Digital Life Balance; GAD-7 = *General Anxiety Disorder 7*; *AAQ-II: Acceptance and Action Questionnaire-II*; *PANAS+: The Positive Affect Scale*; *PANAS-: The Negative Affect Scale*; SWLS: Satisfaction with Life Scale; SAS: Smartphone Addiction Scale; *SME-Q: Social Media Engagement Questionnaire*; *BPS: Bedtime Procrastination Scale*.

Table 5. Descriptive statistics for GAD − 7 severity levels.

Group	*N*	*M*	*SD*
Minimal	80	18.75	6.29
Mild	144	16.17	5.62
Moderate	89	14.15	5.52
Severe	37	13.46	5.34

GAD-7: General Anxiety Disorder 7; Minimal: GAD − 7 score from 0 to 4; Mild: GAD − 7 score from 5 to 9; Moderate: GAD − 7 score from 10 to 14; Severe: GAD − 7 score from 15 to 21.

plot also showed no deviation from normality. Finally, a significant difference was found between the DLB and GAD − 7 categories, $F(3, 346) = 11.71$, $p < 0.001$, $\eta^2 = 0.092$, $\omega^2 = 0.08$. Post hoc analysis revealed that the Minimal Anxiety group had significantly higher DLB scores than the Mild Anxiety ($MD = 2.58$, $p = 0.008$), Moderate Anxiety ($MD = 4.60$, $p < 001$), and Severe Anxiety ($MD = 5.29$, $p < 0.001$) groups. The Mild Anxiety group also had significantly higher DLB scores than the Moderate Anxiety ($MD = 2.03$, $p = 0.045$) and Severe Anxiety ($MD = 2.71$, $p = 0.05$) groups. Lastly, the difference between the Mild Anxiety and Severe Anxiety groups did not reach significance.

ROC analysis (see Figure 2) revealed an area under the curve (AUC) of 0.649 (95% CI 0.59–0.71), indicating that the DLB score has a modest ability to distinguish between lower and higher levels of anxiety. Based on Youden's index, the optimal cutoff score for DLB was 17.5, yielding a sensitivity of 73% and a specificity of 47.38%. These results suggest that there is a moderate association between lower DLB scores and higher levels of anxiety.

4. Discussion

In an era of pervasive digital connectivity (DataReportal, 2025b), the distinction between functional and dysfunctional use of ICT has become increasingly blurred. While ICT can enhance communication, productivity, and access to services, excessive or maladaptive use can disrupt the balance between virtual and offline experiences, with negative consequences for well-being (Duradoni et al., 2022). The construct of DLB has emerged as a valuable tool for assessing individuals' subjective ability to maintain a harmonious integration of digital and real-world activities. Building on previous work conducted in other countries, the current study aimed to validate the Ukrainian adaptation version of the DLB scale.

CFA analysis further confirmed the scale's unidimensional structure, consistent with findings from the original Italian version (Duradoni et al., 2022) and subsequent replications in Brazilian, Turkish, and Russian cultural contexts (Lima-Costa et al., 2024; Soysal et al., 2024; Tosti et al., 2026). The recommended threshold value was met for all of the standardized factor loadings (Hair et al., 2006) in line with the original study and subsequent validation (Duradoni et al., 2022; Lima-Costa et al., 2024; Soysal et al., 2024; Tosti et al., 2026), and together with the satisfactory reliability estimates, these results indicate sufficient internal consistency of the Ukrainian version in the measurement of the construct of the digital life balance. The multigroup CFA for gender supported configural, metric, scalar, and strict

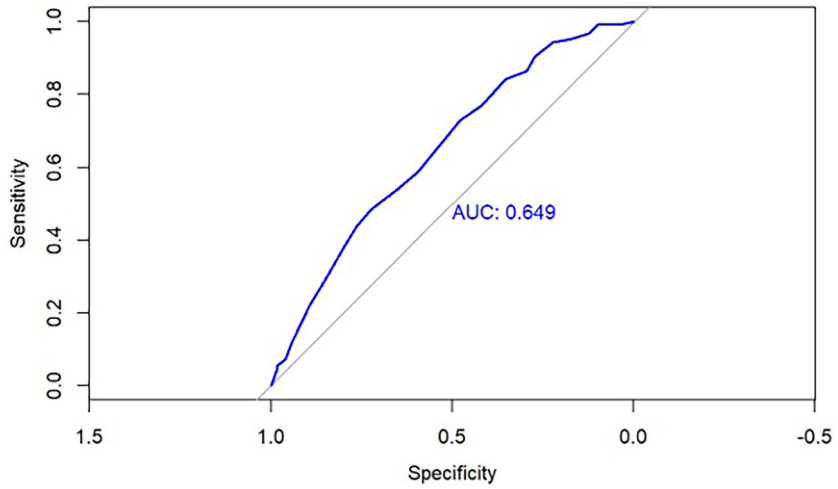


Figure 2. ROC curve for DLB and anxiety.

invariance, proving the scale to be a meaningful tool for assessing perceived online/offline balance across gender. Nevertheless, while configural and metric invariance were achieved across the two age groups of younger and older adults, scalar invariance was not. However, as metric invariance was reached, meaningful comparisons are still possible (Meredith, 1993).

Consistent with previous findings, higher DLB scores were positively associated with constructs indicative of psychological well-being, including life satisfaction and positive emotions, and negatively associated with constructs related to ICT-related maladaptive behaviors and reduced well-being, such as addiction, anxiety, negative emotions, and excessive social media engagement (Duradoni et al., 2022; Lima-Costa et al., 2024; Soysal et al., 2024; Tosti et al., 2026). In addition, the newly investigated variables behaved as hypothesized: psychological inflexibility and bedtime procrastination were both negatively correlated with DLB scores, further supporting the validity of the scale. The correlation with bedtime procrastination reflects how digital overuse can interfere with daily routines and health-related behaviors. The association with psychological flexibility also suggests that individuals with greater adaptive capacity are better able to manage their digital engagement effectively, a finding that is consistent with the theoretical underpinnings of the psychology of harmonization (Di Fabio & Tsuda, 2018).

The ANOVA results provide further insight into how participants with minimal anxiety symptoms reported significantly higher DLB scores than those with mild, moderate, or severe symptoms. Once again, this supports the notion that digital life imbalance may be both a correlate and a contributor to increased psychological distress. Although causality cannot be inferred from the current cross-sectional design, these findings highlight the need for future longitudinal or experimental studies to investigate whether interventions aimed at improving digital life balance could alleviate anxiety symptoms or prevent their escalation. Moreover, ROC analysis indicated that the DLB score has a modest ability to differentiate between individuals with lower and higher anxiety levels. These findings suggest a moderate association between poor digital life balance and elevated anxiety symptoms.

The results of this study have several other practical implications beyond psychometric validation. First, the Ukrainian version of the DLB scale may provide researchers, clinicians, and educators with a brief, reliable, and culturally appropriate tool for assessing individuals' ability to adopt a balanced utilization of ICT. As digital engagement continues to increase (especially among younger populations), having valid measures to detect imbalance could be helpful for both prevention and intervention. For mental health professionals, the DLB scale can serve as a tool to identify individuals whose psychological distress may be related to maladaptive digital behaviors. Tailored interventions could be integrated into broader therapeutic frameworks to address digital life balance by promoting digital awareness and self-regulation. Educational institutions and youth programs could also use the DLB scale to assess students' digital perceived habits about their ICT involvement and support healthier technology practices through media literacy initiatives or well-being workshops.

Ultimately, by offering a validated tool to assess digital life balance, this study supports the development of evidence-based strategies that help individuals, communities, and systems better navigate the challenges of life in a hyper-connected world.

4.1. Limitation and conclusion

Despite the findings that describe the adapted Ukrainian version of the DLB as a suitable measure for assessing individuals' perceptions of their balanced use (or non-use) of ICT, the study has several limitations. First, the cross-sectional design limits the ability to establish causal relationships between variables. Future studies should consider using experimental designs to explore these relationships in more depth. In addition, participants were recruited using non-probability sampling, which limits the generalizability of the results. Further research should aim for more diverse and representative samples to reduce sampling bias. Furthermore, respondent recall bias or social desirability bias may be introduced by the exclusive use of self-report measures. Later investigations could include objective measures to reduce this risk. Another limitation is the lack of test-retest reliability, which would provide insight into the reliability of the scale. The inclusion of follow-up assessments in additional studies could help to assess the consistency of the measure over time. Finally, the ongoing war in Ukraine may have affected how the participants used ICT, as well as distorting their perceptions and responses. Changes in daily routines and anxiety levels brought about by the conflict may not accurately reflect individuals' habits and balance in their use of technology. Future research should take the ongoing war into account when interpreting responses. However, despite these limitations, the Ukrainian version of the DLB scale demonstrated good validity and reliability as a measure of digital life balance.

Author contributions

CRediT: **Anna Enrica Tosti**: Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Anastasiia Shyroka**: Conceptualization, Data curation, Investigation, Methodology, Supervision, Writing – review & editing; **Anastasiia Chorna**: Investigation, Writing – original draft, Writing – review & editing; **Andrea Guazzini**: Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing; **Mirko Duradoni**: Conceptualization, Data curation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing.

Informed consent statement

Informed consent was obtained from all subjects involved in the study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Institutional Review Board statement

The study was conducted in accordance with the Declaration of Helsinki. Ethical approval was waived for this study since this was an anonymous survey with no personal data that could lead to participants identification. All data collected were completely anonymous to ensure confidentiality, in accordance with the EU General Data Protection Regulation (2016/679).

ORCID

Anna Enrica Tosti http://orcid.org/0009-0004-3884-4951
Anastasiia Shyroka http://orcid.org/0000-0002-5265-2794
Anastasiia Chorna http://orcid.org/0009-0001-9399-749X
Andrea Guazzini http://orcid.org/0000-0002-0203-4461
Mirko Duradoni http://orcid.org/0000-0001-8272-9484

Data availability statement

The data presented in this study are available on request from the corresponding author.

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About the authors

Anna Enrica Tosti is a PhD candidate in Experimental and Clinical Geriatrics. Since 2022, she has collaborated with VirtHuLab, applying her expertise in programming and app development to create innovative health assessment tools. Her main interests include cognitive aging and the validation of psychometric instruments for psychological assessment.

Anastasiia Shyroka, is an Associate Professor in the Department of Psychology and Psychotherapy at the Ukrainian Catholic University. Her academic interests focus on trauma, emotional regulation, and war-related experiences. She is actively involved in developing training programs and psychological support initiatives in Ukraine.

Anastasiia Chorna is a master's student in Clinical Psychology with a CBT-based specialization at the Ukrainian Catholic University. Her main interests include the validation of psychometric instruments and the assessment of quality of life across different populations.

Andrea Guazzini, Associate Professor at the FORLILPSI Department, University of Florence, directs VirtHuLab (CSDC). His research interests include social cognition, virtual dynamics, cognitive psychology, and neuropsychology, integrating statistical mechanics and nonlinear physics into psychology. He has authored approximately 120 peer-reviewed international journal articles (180 total publications).

Mirko Duradoni is currently a researcher in Social Psychology at Mercatorum University (Rome). He holds a master's degree in Psychology and a PhD in Information Engineering. His research focuses on psychological assessment, research methods, data analysis, digital well-being, and psychology of harmony.

Appendix A

Table A1. Translated Ukrainian items of the Digital Life Balance scale.

	Прочитайте кожне твердження і оцініть наскільки воно вас описує. Перед вами буде 4 твердження, які потрібно оцінити від 1 (повністю не погоджуюся) до 7 (повністю погоджуюся)	повністю не погоджуюся						повністю погоджуюся
1	Наразі у мене хороший баланс між часом, який я проводжу онлайн, і часом, який я маю для офлайн активностей.	1	2	3	4	5	6	7
2	Мені важко збалансувати свій час онлайн та офлайн.	1	2	3	4	5	6	7
3	Я вважаю, що баланс між моєю онлайн та офлайн активністю на цей час є правильним.	1	2	3	4	5	6	7
4	В цілому, я вважаю, що моє життя онлайн та офлайн збалансоване	1	2	3	4	5	6	7