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DIGITAL BURNOUT IN NURSING: DEVELOPMENT OF A VALID AND RELIABLE SCALE TO ASSESS DIGITAL BURNOUT ASSOCIATED WITH THE DIGITALIZATION PROCESS IN NURSING

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Abstract

Objectives: This study aimed to develop a valid and reliable scale to assess digital burnout associated with the digitalization process in nursing and to examine its relationship with organizational stress.

Methodology: This methodological and cross-sectional study was conducted with 302 nurses in a public hospital in Hatay, Turkey. The dataset was randomly divided into two independent subsamples to ensure robust construct validation. Exploratory Factor Analysis (EFA) was performed on one subsample (n = 151), followed by Confirmatory Factor Analysis (CFA) on the other (n = 151). Internal consistency and reliability were assessed using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Pearson correlation and Structural Equation Modeling (SEM) were performed to examine relationships among variables.

Findings: The analyses revealed a two-factor structure consisting of 16 items, namely Emotional Exhaustion and Erosion of Human Interaction. The scale demonstrated high internal consistency, with Cronbach's alpha values ranging from 0.93 to 0.96. CR and AVE supported both convergent and discriminant validity. Correlation analysis indicated a positive relationship between digital burnout and organizational stress ($r = 0.28$, $p < 0.01$). SEM results showed that erosion of human interaction significantly predicted both emotional exhaustion ($\beta = 0.776$, $p < 0.001$) and organizational stress ($\beta = 0.287$, $p < 0.001$), whereas emotional exhaustion did not significantly predict organizational stress and was excluded from the final model.

Conclusions: The Digital Burnout Scale in Nursing was found to be a valid and reliable instrument for assessing burnout experiences related to the digitalization process in nursing practice. The findings suggest that digital burnout is a multidimensional construct primarily driven by interaction-related disruptions in digital work environments.

Implications: The scale provides a context-specific tool for assessing digital burnout in nursing and contributes to the distinction between technostress and burnout. It can be used by healthcare administrators, researchers, and nurses to identify and monitor risks related to digital workload and support early recognition of burnout. At the organizational level, the scale can inform targeted interventions, such as improving system usability, reducing documentation burden, and strengthening organizational support, thereby contributing to nurse well-being and quality of care.

Keywords: Nurses; Digital burnout; Digitalization in nursing; Scale development; Psychometric properties; Organizational stress.

1. INTRODUCTION

Population aging, the increasing prevalence of chronic diseases, and rising demand for healthcare services continue to place a substantial burden on existing systems [1, 2]. In recent years, large-scale crises such as the COVID-19 pandemic [3] and the February 6 earthquakes in Türkiye have further underscored the fragility of healthcare services and their vulnerability to sudden and prolonged disruptions [4]. In response to these challenges, digital solutions have played an increasingly prominent role in ensuring the continuity of healthcare delivery [5, 6]. Electronic health records, telemedicine applications, and mobile health technologies have emerged as key tools for maintaining uninterrupted healthcare services, particularly during periods of crisis and system overload [7]. However, while digitalization has facilitated healthcare delivery, it has also introduced additional workload and complexity for healthcare professionals [8, 9]. The mandatory integration of digital systems into daily clinical workflows has contributed to increased workload and expanded routine responsibilities [10]. This burden is particularly evident among healthcare professionals who must balance direct patient care with growing digital demands [11]. For nurses, these additional digital tasks are no longer occasional but are embedded in everyday care delivery [12].

Electronic medical records, patient portals, and similar systems facilitate communication and access to information [13]. At the same time, their continuous use places additional demands on healthcare professionals [14, 15]. These systems require sustained attention to documentation, data management, and digital communication alongside routine nursing responsibilities [14, 16, 17]. Nurses are among the healthcare professionals most affected because their routine clinical work requires continuous interaction with digital systems [18, 19]. Studies suggest that the use of digital technologies in nursing is associated with increased stress and emotional exhaustion [18, 20]. Prolonged exposure to digital systems, combined with high job demands, has been shown to intensify psychological strain and contribute to burnout-related experiences among nurses [13, 21].

The negative effects of digital technologies are commonly examined within the framework of technostress [22, 23]. Burnout in nursing is widely conceptualized as a response to prolonged work-related stress [24]. Recent studies suggest that sustained interaction with technological systems may give rise to digital burnout, a more specific form of occupational strain associated with prolonged exposure to digital work demands [15, 25–28].

Organizational stress constitutes another important dimension of nurses' work experiences. Workload, time pressure, staffing shortages, and limited managerial support are well-established sources of stress in nursing [29–31]. The relationships examined in this study are grounded in the Job Demands–Resources Model (JD-R model) [32], which proposes that high job demands may lead to exhaustion when adequate resources are lacking [33]. In digital healthcare environments, continuous interaction with electronic systems may function as a persistent job demand, whereas limited system usability, insufficient training, and organizational constraints may reduce available resources [34, 35]. Broader digital transformation frameworks in healthcare similarly emphasize that technological change reshapes both organizational processes and employees' work experiences [36, 37]. Accordingly, digital burnout can be understood as a context-specific outcome arising from an imbalance between increasing digital work demands and insufficient organizational and personal resources [38, 39].

Despite growing research on the effects of digitalization in healthcare, the existing literature remains conceptually fragmented and does not adequately capture digital burnout as a distinct phenomenon in nursing practice [22, 40]. In addition, many available instruments were developed in students or general population samples and may not adequately reflect the continuous, mandatory, and workflow-integrated nature of digital system use in nursing [41–43]. Consequently, there is a clear need for a psychometrically sound instrument specifically designed to assess digital burnout among nurses.

The aim of this study was to develop a valid and reliable scale to assess digital burnout in nursing and to examine its relationship with organizational stress. By introducing a context-specific measurement tool, the study seeks to make the effects of digitalization in nursing more visible and to address an important gap in the existing literature.
Accordingly, the study was guided by the following research questions:

RQ1: Does digital burnout in nursing demonstrate a multidimensional structure consistent with the proposed theoretical framework?

RQ2: Does the Digital Burnout Scale in Nursing exhibit adequate internal consistency at the subscale level?

RQ3: Do the construct validity indicators of the Digital Burnout Scale in Nursing meet acceptable psychometric criteria?

RQ4: Is digital burnout among nurses significantly associated with organizational stress?

In line with these research questions, the following hypotheses were formulated:

H1: Digital burnout in nursing demonstrates a multidimensional structure consistent with the proposed theoretical framework.

H2: The Digital Burnout Scale in Nursing exhibits adequate internal consistency at the subscale level.

H3: The Digital Burnout Scale in Nursing meets acceptable construct validity criteria, including convergent and discriminant validity.

H4: Digital burnout among nurses is positively and significantly associated with organizational stress.

2. METHODS

This study was designed as a methodological and cross-sectional study. Methodological approaches are commonly employed in scale development research to establish the psychometric properties of newly developed instruments [44, 45]. Furthermore, cross-sectional designs are widely used in health research to examine relationships between variables at a single point in time and to provide a snapshot of the study population, thereby supporting the identification of associations and patterns [46, 47].

2.1. Research Design

The study was carried out in a public hospital in Hatay Province, Turkey. It was designed as a scale development study to assess nurses' experiences of digital burnout in the context of ongoing digitalization in healthcare. A methodological and cross-sectional design was employed.

2.2. Participants and Sampling

Data were collected from nurses actively working at a public hospital located in Hatay Province, Turkey. Participants were required to be actively employed as nurses at the participating hospital, to have provided voluntary consent to take part in the study, to possess basic digital skills necessary for completing the online questionnaire, and to have completed the survey in full. Participants were able to proceed with the survey only after indicating their informed consent by selecting the voluntary participation checkbox presented at the beginning of the questionnaire. All eligible nurses working at the hospital during the study period were invited to participate.

The sample size was determined in accordance with established recommendations for scale development studies, suggesting a minimum of 5–10 participants per item. Accordingly, an adequate sample size was targeted for the initial 25-item draft scale, and data collection was completed with 302 nurses. At the time of the study, a total of 468 nurses were employed at the hospital, according to information obtained from hospital administration. Of these, 302 nurses agreed to participate and completed the questionnaire, yielding a participation rate of 64.5%.

To test construct validity, the dataset was randomly divided into two subsamples using SPSS software. The randomization process was conducted using the random sampling function in SPSS to ensure unbiased allocation of participants into subsamples [48]. This approach was adopted to prevent overfitting and to ensure that the factor structure identified in the exploratory phase could be independently validated in a separate sample [49, 50]. Using independent subsamples for EFA and CFA is recommended to enhance the robustness and generalizability of scale development studies [51–53]. Exploratory Factor Analysis was conducted with 151 participants, while Confirmatory Factor Analysis was performed with the remaining 151 participants. Conducting factor exploration and confirmation on independent subsamples was intended to enhance the generalizability and robustness of the proposed measurement model.

2.3. Data Collection Instruments

Data were collected using a Personal Information Form, the Digital Burnout Scale in Nursing (DBSN), and the Organizational Stress Scale.

Personal Information Form: A personal information form developed by the researchers was used to collect participants' sociodemographic and professional characteristics. The form included items on age, unit or department of employment, gender, marital status, level of professional education, perceived monthly income level, years of professional experience, average weekly working hours, prior training related to digitalization, and average daily screen time.

Digital Burnout Scale in Nursing (DBSN): The Digital Burnout Scale in Nursing (DBSN) was newly developed specifically for this study, and the full English version of the scale items is provided as Supplementary Material 1. In the initial phase of scale development, a systematic review of national and international literature on digitalization, digital transformation, digital workload, technology-related stress, and burnout was conducted. The literature search was performed using Google Scholar, Elsevier, PubMed, Web of Science, Scopus, and DergiPark databases. Based on the resulting theoretical framework, an initial item pool consisting of 25 items was generated to reflect nurses' experiences related to digitalization.

To evaluate the content validity of the draft scale, expert opinions were obtained from a total of nine experts, including two associate professors specializing in measurement and evaluation, four expert nurses working in clinical settings, and three faculty members employed in nursing faculties. Experts were provided with evaluation forms to rate each item according to the Davis technique. Following expert review, content validity indices were calculated, and one item that fell below acceptable thresholds and was deemed insufficiently representative of the target construct was removed. As a result, the scale was reduced to a 24-item preliminary form.

A pilot study was conducted with 27 nurses to assess the applicability and preliminary reliability of the scale. The pilot study was conducted to evaluate the clarity, comprehensibility, and applicability of the scale items prior to the main data collection [54]. It also aimed to identify potential ambiguities and ensure that the items adequately reflected the intended construct [55]. To examine temporal stability, the test–retest method was employed, and the scale was re-administered to the same participants after a 12-day interval [56]. To enable matching of responses without collecting identifiable information, participants were asked to create a four-digit matching code known only to themselves. The same code was entered during the second administration to ensure accurate pairing of responses.

Consistency between the two measurements was evaluated using the Intraclass Correlation Coefficient (ICC), which was calculated as 0.816 and found to be statistically significant ($p < 0.001$) [57]. Only participants who completed both administrations and whose responses could be matched using the code were included in the analysis. During the pilot phase, participants were also asked whether any items were unclear or required modification; based on their feedback, minor linguistic revisions were made without altering the substantive meaning of the items. The scale items were rated on a five-point Likert scale ranging from "never," "very rarely," "sometimes," "often," to "always." Following content validity assessment, the items were subjected to factor analysis to examine construct validity. Higher scores indicate higher levels of digital burnout.

Organizational Stress Scale: Organizational stress was assessed using the previously published and validated Organizational Stress Scale, adapted into Turkish by Yıldırım et al. in 2011 [58]. The continued use of this scale is supported by recent studies conducted in different occupational groups, indicating its applicability across various professional contexts [59]. The scale consists of 14 items and four subscales. Items 1, 2, 3, 5, and 6 are positively worded, while the remaining items are reverse coded. Responses are rated on a five-point Likert scale ranging from “never” to “always.” In the original validation study, the Cronbach’s alpha coefficient was reported as 0.79; in the present study, internal consistency was 0.744.

2.4. Data Collection

Following ethical approval and completion of the pilot study, data collection was conducted online via Google Forms between 17 December 2025 and 21 January 2026. The survey link was distributed through the relevant hospital units.

The use of an online, self-administered questionnaire enabled standardized data collection and reduced the potential for interviewer-related bias. Participation in the study was voluntary. Before accessing the questionnaire, participants were presented with a brief information note and were able to proceed only after confirming their voluntary participation. No IP addresses, identity information, or other personally identifiable data were collected, and confidentiality was ensured throughout the data collection process.

At the end of the data collection period, only fully completed and valid questionnaires were included in the analyses. The average completion time of the survey was approximately 8–10 minutes.

2.5. Statistical Analysis

Data analyses were performed using IBM SPSS Statistics version 26 and AMOS version 24. The measurement and structural models were evaluated using covariance-based structural equation modeling (CB-SEM). Although newer versions are available, these versions remain widely used in recent research and provide the necessary analytical procedures for multivariate analysis and structural equation modeling [60, 61]. Descriptive statistics were used to summarize the sociodemographic and professional characteristics of the participants, including age, gender, marital status, unit or department of employment, years of professional experience, prior training related to digitalization, and average daily screen time. The statistical analysis plan was determined in advance. Exploratory and confirmatory factor analyses were conducted to evaluate the construct validity of the scale.

Internal consistency and reliability were examined using Cronbach's alpha, composite reliability, and average variance extracted. Finally, Pearson correlation analysis was applied to examine the relationship between digital burnout and organizational stress.

To examine construct validity during the scale development process, the dataset was randomly divided into two subsamples. Splitting the sample for Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) was preferred to reduce the risk of overfitting and to provide a more robust evaluation of construct validity. EFA was carried out on the first subsample (n = 151). Prior to EFA, the suitability of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity [57]. All scale scores were treated as continuous variables. Item scores were summed and averaged according to their respective subdimensions and total scale structure. No categorization or dichotomization of continuous variables was performed. Higher scores indicated higher levels of digital burnout and organizational stress.

EFA was performed using the Principal Axis Factoring method, and Direct Oblimin rotation was applied to allow for correlations among factors [53]. A factor loading cut-off value of 0.40 was adopted for item retention. For items loading on more than one factor, a minimum difference of 0.10 between factor loadings was required. Items that did not meet these criteria were removed from the analysis.

The EFA was carried out in an iterative manner, with item removal decisions guided by both statistical criteria and the theoretical coherence of the construct under investigation. The factor structure derived from the EFA was then applied to the second subsample and examined using Confirmatory Factor Analysis (CFA) [62, 63].

CFA was performed on the second subsample of 151 participants using the maximum likelihood estimation method. Model fit was assessed by jointly considering absolute and incremental fit indices. The final measurement model was determined through an integrated evaluation of theoretical consistency and CFA results, with particular attention given to indicators that adversely affected model fit. Following the evaluation of the measurement model, a structural model was specified to test the relationships between the dimensions of digital burnout and organizational stress. In the structural model, erosion of human interaction was specified as a predictor of both emotional exhaustion and organizational stress, while emotional exhaustion was also tested as a predictor of organizational stress. Model fit for both the measurement and structural models was evaluated using standard fit indices, including χ^2/df, CFI, TLI, and RMSEA, in line with established SEM procedures in the literature [64].

To assess internal consistency, Cronbach's alpha coefficients were calculated for the scale and its subscales. In addition, composite reliability (CR) and average variance extracted (AVE) values were computed to provide a more detailed evaluation of the psychometric properties of the measurement model. Discriminant validity was assessed by comparing the correlations between subscales with the square root of the AVE values [65, 66].

To examine the distributional characteristics of the scale and its subscales, mean, standard deviation, skewness, and kurtosis values were calculated. Skewness and kurtosis values within the range of ±1.5 were considered indicative of acceptable normality [62, 67]. Accordingly, the assumptions required for the use of parametric tests were considered to be met, and parametric analyses were applied in subsequent analyses.

The relationship between digital burnout in nursing and organizational stress was examined using Pearson correlation analysis. Across all analyses, statistical significance was defined as a p value below 0.05.

2.6. Ethical Considerations

Ethical approval for the study was obtained from the Hatay Mustafa Kemal University Social and Human Sciences Scientific Research and Publication Ethics Committee (Decision No. 2025/19). The study was conducted in accordance with the principles of the Declaration of Helsinki.

3. RESULTS

3.1. Sociodemographic Characteristics of Participants

The sociodemographic and professional characteristics of the participants are presented in Table 1. An examination of the age distribution showed that 46.0% of the participating nurses were aged 18–29 years, followed by those aged 30–44 years (39.1%). The majority of participants were female (73.2%), and 63.9% reported being married. With regard to educational level, 63.9% of the nurses held a bachelor's degree.

In terms of professional characteristics, most participants were employed in emergency and intensive care units (29.5%), followed by surgical and operating room units (26.8%). Regarding professional experience, 35.4% of the nurses had been working in the profession for 1–5 years, while 30.8% reported 6–10 years of experience.

Findings related to working conditions indicated that a substantial proportion of participants worked 41–50 hours per week (44.4%). In the assessment of income level, 67.9% of nurses described their income as moderate. With respect to digitalization-related characteristics, 57.3% of participants reported that they had not received any prior training related to digitalization, whereas 51.3% stated that they spent approximately 3–4 hours per workday in front of a screen during working hours.

Table 1. Sociodemographic and Professional Characteristics of the Study Sample (N = 302)

Sociodemographic / Professional Characteristics	Groups	N	%
Age	18–29 years	139	46.0
	30–44 years	118	39.1
	45–60 years	45	14.9
Gender	Female	221	73.2
	Male	81	26.8
Marital status	Married	193	63.9
	Single	109	36.1
Educational level	High school	91	30.1
	Bachelor's degree	193	63.9
	Master's degree	18	6.0
Unit of employment	Emergency and Intensive Care Units	89	29.5
	Surgical and Operating Room Units	81	26.8
	Internal Medicine and Specialty Units	42	13.9
	Obstetrics–Gynecology and Pediatric Units	55	18.2
	Rehabilitation and Administrative Units	35	11.6
Years of professional experience	1–5 years	107	35.4
	6–10 years	93	30.8
	11–15 years	42	13.9
	≥16 years	60	19.9
Average weekly working hours	≤30 hours	5	1.7
	31–40 hours	108	35.8
	41–50 hours	134	44.4
	51–60 hours	45	14.9

	≥61 hours	10	3.3
Perceived monthly income level	Poor	75	24.8
	Moderate	205	67.9
	Good	22	7.3
Previous training on digitalization	Yes (in-service)	92	30.5
	Yes (external)	37	12.3
	No	173	57.3
Screen time during working hours	<1 hour	21	7.0
	1–2 hours	89	29.5
	3–4 hours	155	51.3
	5–6 hours	37	12.3

3.2. Measurement Model Evaluation (Outer Model)

3.2.1. Construct Validity: Exploratory Factor Analysis (EFA) (N = 151)

The measurement model was evaluated using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and reliability and validity analyses. In this context, EFA was conducted to examine the construct validity of the scale [53]. The analysis was performed on a sample of 151 participants. The suitability of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The KMO value was found to be 0.945, indicating excellent sampling adequacy for factor analysis. Bartlett's test of sphericity yielded a significant result ($\chi^2(190) = 2816.431$, $p < 0.001$), demonstrating the presence of sufficient correlations among variables to justify factor analysis [68]. Based on these findings, the dataset was considered appropriate for EFA.

EFA was performed using the Principal Axis Factoring method, and Direct Oblimin rotation was applied to allow for correlations among factors [69]. A factor loading cut-off value of 0.40 was adopted for item retention. For items loading on more than one factor, a minimum difference of 0.10 between factor loadings was required. Items that did not meet these criteria were excluded from the analysis.

The EFA process was conducted iteratively, with both statistical criteria and theoretical considerations taken into account. In this process, factors consisting of only two items and lacking theoretical coherence, as well as items with low factor loadings, were removed from the analysis (A13 and A14). Following their removal, subsequent analyses identified items that loaded similarly on more than one factor and failed to meet the 0.10 loading difference criterion; these items were excluded due to cross-loading issues (A21 and A24). In later stages, items forming a single-factor solution without supporting theoretical coherence (A11), as well as items showing comparable loadings on two factors and lacking discriminative capacity (A3 and A19), were also removed. After each item removal, the factor analysis was re-run, and decisions were made while preserving the theoretical integrity of the construct being measured.

As presented in Table 2, the EFA results revealed a two-factor structure comprising 17 items following the stepwise elimination process. In the final EFA model, the first factor comprised eight items (A20, A16, A17, A15, A23, A18, A22, and A12), while the second factor consisted of nine items (A5, A6, A1, A10, A9, A7, A2, A8, and A4).

Based on item content and the underlying theoretical framework, the first factor was labeled Emotional Exhaustion, and the second factor was labeled Erosion of Human Interaction. As presented in Table 2, all factor loadings exceeded the acceptable threshold of 0.40. In addition, communality values were within acceptable ranges, indicating that a substantial proportion of variance in each item was explained by the extracted factors. No reverse-coded items were included in the scale.

Following the item elimination process, cross-loading values were re-examined based on the pattern matrix results. All retained items demonstrated higher loadings on their intended factors than on the alternative factor, with differences exceeding the recommended threshold of 0.10. These findings indicate the absence of cross-loading issues and provide support for the discriminant validity of the factor structure.

Table 2. Factor Loadings and Explained Variance of the Scale

Scale Items	**CVI**	**F1**	**F2**
A20	1.00	0.960	
A16	1.00	0.831	
A17	1.00	0.813	
A15	0.83	0.766	
A23	1.00	0.759	
A18	1.00	0.757	

A22	1.00	0.742	
A12	1.00	0.733	
A5	1.00		0.957
A6	1.00		0.870
A1	1.00		0.862
A10	0.83		0.802
A9	1.00		0.667
A7	1.00		0.653
A2	0.83		0.636
A8	0.83		0.582
A4	1.00		0.509
Eigenvalue		10.329	1.485
% of variance		60.757	8.736
Cumulative %		**60.757**	**69.494**

Note. Items with factor loadings greater than 0.40 were retained.

To further evaluate the measurement model, cross-loading values are presented in Table 3.

Table 3. Cross-loadings of the scale items

Item	**EE**	**EHI**
A20	0.960	-0.102
A16	0.831	0.021
A17	0.813	0.053
A15	0.766	0.043
A23	0.759	0.108
A18	0.757	0.051
A22	0.742	-0.038
A12	0.733	0.104
A5	-0.164	0.957
A6	-0.024	0.870

A1	-0.013	0.862
A10	-0.029	0.802
A9	0.155	0.667
A7	0.161	0.653
A2	0.207	0.636
A8	0.167	0.582
A4	0.323	0.509

Note. Cross-loading values are derived from the final EFA solution prior to CFA-based item refinement.

The results indicate that each item loads more strongly on its respective factor than on the alternative factor, with sufficient differences between loadings. This confirms that cross-loading is not a concern and further supports the discriminant validity of the measurement model.

3.2.2. Confirmatory Factor Analysis (CFA) (N = 151)

The two-factor structure identified through Exploratory Factor Analysis (EFA) was tested using Confirmatory Factor Analysis (CFA). Analyses were conducted using the maximum likelihood estimation method. Although item A23 demonstrated acceptable factor loadings during the EFA phase, it was found to weaken model fit and produce high modification indices in the CFA. Therefore, item A23 was removed from the final model, with both statistical criteria and theoretical coherence taken into consideration. This refinement process reflects the iterative nature of scale development, where decisions regarding item retention are guided by both statistical criteria and theoretical considerations to achieve a more parsimonious model with improved fit. Following this modification, the scale was reduced to a final structure consisting of two subdimensions and a total of 16 items, and all subsequent evaluations were conducted based on this final measurement model.

The model fit indices obtained were as follows: $\chi^2/df = 1.908$, CFI = 0.957, TLI = 0.950, IFI = 0.958, NFI = 0.915, RMSEA = 0.078, and RMR = 0.053. The CFI, TLI, and IFI values exceeding the 0.90 threshold indicate a good level of model fit. In addition, a χ^2/df

ratio below 2.0 and an RMR value below the 0.08 threshold further support that the measurement model demonstrates an adequate fit to the data [70, 71]. In addition, RMSEA values between 0.05 and 0.08 are generally considered indicative of acceptable model fit, in line with commonly accepted and recently discussed criteria in the structural equation modeling literature [72, 73].

As shown in Figure 1, the standardized factor loadings in the final CFA model ranged from 0.722 to 0.887, and all loadings were statistically significant ($p < 0.001$). The Emotional Exhaustion subdimension consisted of seven items, whereas the Erosion of Human Interaction subdimension comprised nine items. Overall, model fit indices and factor loadings indicate that the two-factor, 16-item model represents a valid structure.

Figure 1. Confirmatory factor analysis (CFA) path diagram of the Digital Burnout in Nursing Scale.

3.2.3. Reliability

In this study, the internal consistency of the scale was examined using Cronbach's alpha coefficients. In the literature, Cronbach's alpha values above 0.70 are considered acceptable, values above 0.80 indicate good reliability, and values of 0.90 or higher are interpreted as reflecting very high levels of reliability [74, 75].

According to the analysis results, the Cronbach's alpha coefficient for the Emotional Exhaustion subdimension (7 items) was calculated as 0.932, while the coefficient for the Erosion of Human Interaction subdimension (9 items) was 0.946. The overall Cronbach's alpha value of the scale was 0.958, indicating that the items represent the measured construct with a high level of internal consistency and reliability.

The fact that all reliability coefficients obtained for both the subdimensions and the total scale exceeded 0.90 demonstrates that the two-factor structure of the scale has high internal consistency and that the measurement results are stable and reliable. Although the high Cronbach's alpha values indicate strong internal consistency, values exceeding 0.90 may also suggest potential item redundancy. This may indicate that some items capture highly similar aspects of the construct, suggesting that future studies may consider item reduction strategies to enhance scale parsimony. Therefore, future studies may consider further refinement or shortening of the scale to enhance its parsimony while maintaining reliability. These results provide support for the reliability of the scale at both the subscale and total score levels.

3.2.4. Convergent and Discriminant Validity

Convergent and discriminant validity of the measurement model were assessed using AVE, CR, √AVE, and HTMT criteria.

Table 4. Convergent and Discriminant Validity Statistics

Subdimension	EE	EHI	CR	AVE	CA	HTMT
EE	0.81	0.76	0.93	0.66	0.93	-
EHI	0.76	0.84	0.95	0.71	0.94	0.803

Note. EE = Emotional Exhaustion; EHI = Erosion of Human Interaction; CR = Composite Reliability; AVE = Average Variance Extracted; CA = Cronbach's alpha. Values on the diagonal represent the square root of AVE (√AVE). The HTMT value between EE and EHI was 0.803, indicating adequate discriminant validity.

The results presented in Table 4 indicate a positive, moderate-to-high correlation between the Emotional Exhaustion (EE) and Erosion of Human Interaction (EHI) subdimensions of the scale (r = 0.76). This result suggests that while the subdimensions are related, they represent distinct aspects of the construct being measured. However, although the square root of AVE values supports discriminant validity, the relatively high correlation between the subdimensions may indicate a degree of conceptual overlap. This level of correlation can be considered acceptable, as both subdimensions arise from the same digital work environment and reflect closely related yet conceptually distinct aspects of digital burnout. Therefore, while the factors capture distinguishable dimensions, their moderate-to-high association suggests that they may partially share common variance without compromising the overall construct validity of the scale.

An examination of the square root of the √AVE values used to assess discriminant validity shows that the √AVE values calculated for both subdimensions (EE = 0.81; EHI = 0.84) are higher than the correlation coefficient between the subdimensions (r = 0.76). This indicates that each subdimension explains its own items more strongly than it explains the other subdimension, thereby supporting the discriminant validity of the scale [76, 77].

The AVE values used to assess convergent validity were found to exceed the 0.50 threshold for both subdimensions (EE = 0.66; EHI = 0.71). These results indicate that the items within each subdimension adequately represent the intended construct and that convergent validity is supported [70, 78, 79].

In addition, composite reliability (CR) values exceeded the recommended threshold of 0.70 for both subdimensions (EE = 0.93; EHI = 0.95), indicating strong internal consistency of the measurement model. These findings further support the internal consistency of the measurement model.

Overall, these results suggest that the scale satisfies both convergent and discriminant validity and that the two-factor structure adequately represents the intended conceptual construct from both statistical and theoretical perspectives.

Table 5. Descriptive Statistics of the Scales

Scale and Subdimensions	**Number of Items**	**Mean**	**SD**	**Skewness**	**Kurtosis**
DBSN	16	3.06	0.82	-0.81	0.43
Emotional Exhaustion	7	3.33	0.88	-1.13	0.94
Erosion of Human Interaction	9	2.85	0.88	-0.50	-0.07
OSS	14	2.89	0.44	1.32	0.92

Note. DBSN = Digital Burnout Scale in Nursing; OSS = Organizational Stress Scale; SD = standard deviation. Skewness and kurtosis values indicate distributional characteristics.

An examination of the descriptive statistics presented in Table 5 indicates that participants' levels of Emotional Exhaustion were at a moderate-to-high level (Mean = 3.33; SD = 0.88). The mean score for the Erosion of Human Interaction subdimension was comparatively lower (Mean = 2.85; SD = 0.88). The overall mean score of the scale (Mean = 3.06) suggests that participants generally experienced a moderate level of burnout and erosion in interaction associated with the digitalization process.

With respect to distributional characteristics, the skewness and kurtosis values calculated for all subdimensions and the total scale were within the range of ±1.5. These results indicate that the assumption of normality was met and that the use of parametric analyses was appropriate [80, 81].

3.3. Structural Model Evaluation (Inner Model)

The structural model examined the relationships between emotional exhaustion, erosion of human interaction, and organizational stress. The results showed that erosion of human interaction was significantly associated with both emotional exhaustion and organizational stress. Only statistically significant paths were retained in the final model. The standardized path coefficients are presented in Table 6.

Table 6. Structural Path Coefficients of the Final SEM Model

Path	β	S.E.	C.R.	p
Erosion of Human Interaction → Emotional Exhaustion	0.776	0.062	13.385	<0.001
Erosion of Human Interaction → Organizational Stress	0.287	0.422	4.990	<0.001

Note. β = standardized regression coefficient; S.E. = standard error; C.R. = critical ratio.

Model fit indices indicated an acceptable fit ($\chi^2/df = 3.41$, CFI = 0.932, TLI = 0.921, RMSEA = 0.090). These findings indicate that erosion of human interaction is more strongly associated with both emotional exhaustion and organizational stress. Figure 2 illustrates the final structural model and the standardized path coefficients between the study variables.

Figure 2. Final Structural Model with Standardized Path Coefficients. Note. ***p < 0.001.

Correlation analysis was conducted to examine the relationship between digital burnout and organizational stress.

Table 7. Correlation Analysis Between Scales

Variables	**1**	**2**
1. Digital Burnout Scale in Nursing	1	0.280**
2. Organizational Stress	0.280**	1

Note. *N* = 302. p < 0.01 (two-tailed).

The correlation analysis presented in Table 7 showed that digital burnout was positively associated with organizational stress ($r = 0.280$, $p < 0.01$). This result is consistent with the structural model and supports the predictive validity of the scale.

4. DISCUSSION

The findings of this study indicate that the Digital Burnout Scale in Nursing (DBSN) is a valid and reliable instrument for assessing burnout experiences related to digitalization among nurses. The results of the exploratory and confirmatory factor analyses support a two-dimensional structure consisting of Emotional Exhaustion and Erosion of Human Interaction. This structure is consistent with the conceptual framework of the study and reflects key aspects of digital burnout in nursing practice. In addition, the positive association between digital burnout and organizational stress indicates that digital burnout is influenced by both individual factors and organizational conditions.

During the scale development process, the subdimensions were named based on both statistical findings and the thematic content of the items. In line with the scale development literature, factor labels were selected to clearly represent the experiences captured by the items [82, 83]. Accordingly, the DBSN captures both emotional strain and the gradual weakening of interpersonal interactions associated with the routine use of digital systems in nursing.

The present study differs from existing digital fatigue and burnout scales, which are generally based on the general population, students, or voluntary digital use contexts [84]. In nursing, digital system use is not optional but an integral part of care delivery. This underscores the need for a context-specific measurement tool. While existing instruments tend to assess general burnout or technology-related stress, they do not fully capture the continuous, mandatory, and workflow-integrated nature of digital work in nursing [72, 85–87]. In contrast, the DBSN focuses directly on burnout experiences arising from sustained interaction with digital systems in clinical settings [12, 88]. This interpretation is also consistent with recent reviews emphasizing that digital technologies have become deeply embedded in nursing workflows and may increase workload and role complexity [10, 89, 90]. Although technostress has been widely used to explain the psychological consequences of workplace technologies, it primarily reflects stress responses associated with adapting to digital systems and managing information overload [22, 23].

The Emotional Exhaustion subdimension reflects experiences such as frequent system updates, technical difficulties, concerns about making errors, increased workload, and feelings of guilt related to digital tasks. These findings are consistent with previous research showing that digital technologies impose emotional as well as cognitive demands on nurses [13, 25]. Prior studies have linked the use of health information technologies to emotional strain, alienation, and increased workload [91–94]. In this sense, the Emotional Exhaustion subdimension captures a form of burnout that extends beyond general fatigue and is closely related to sustained digital workload.

The second subdimension, Erosion of Human Interaction, reflects changes in the nurse–patient relationship associated with digitalization. It encompasses reduced communication, limited face-to-face interaction, and challenges in maintaining empathic engagement. The findings align with previous studies indicating that electronic documentation systems can reduce direct patient interaction and may weaken the humanistic aspects of care [8, 87, 95, 96]. In addition, the increasing focus on digital interfaces may constrain patient-centered care practices. Although recent evidence on this issue remains limited, existing studies suggest that digitalization can affect both communication and care quality [96, 97]. Within this context, the concept of Erosion of Human Interaction captures a distinct aspect of digital burnout related to relational and communicative processes.

The structural model provides further insight into the relationship between digital burnout and organizational stress. Erosion of Human Interaction emerged as a significant predictor of both emotional exhaustion and organizational stress, whereas emotional exhaustion did not significantly predict organizational stress. This finding suggests that disruptions in interpersonal interaction may play a more central role in explaining organizational stress than individual emotional strain alone. In digitalized work environments, limitations in communication and reduced patient contact may represent a more immediate and visible source of stress.

Organizational stress is closely linked to working conditions and job demands. Although the Organizational Stress Scale does not specifically address digitalization, it captures core workplace pressures such as workload, time constraints, performance expectations, and limited organizational support. When combined with digital work demands, these factors may intensify stress and contribute to burnout. This interpretation is consistent with previous research showing that workload and organizational pressures negatively affect both nurse well-being and the quality of care [29, 98]. Similarly, studies indicate that digital systems can increase workload and time pressure, thereby contributing to stress and psychosocial strain [91, 99].

From a theoretical perspective, these findings can be interpreted within the framework of the Job Demands–Resources (JD-R) model [100–103]. Continuous interaction with digital systems may function as a job demand that gradually depletes psychological resources. At the same time, limited system usability and insufficient digital support may restrict available resources. In this sense, digital burnout can be understood as a context-specific form of occupational strain shaped by digital work environments.

These findings are also consistent with broader digital transformation frameworks in healthcare, which emphasize that technological change reshapes both organizational processes and employees' work experiences [36, 104]. In line with these frameworks, the present study demonstrates that digital technologies influence clinical workflows and shape the psychosocial conditions under which nurses work. This perspective supports the conceptualization of digital burnout as a specific occupational outcome associated with the ongoing digital transformation of healthcare services.

This study contributes to the literature by conceptualizing digital burnout as a distinct construct in nursing and by situating it within a structured theoretical framework. The findings extend existing models of occupational stress to digitalized healthcare settings. The findings also align with emerging conceptual work highlighting the importance of digital resilience and adaptation among nurses working in increasingly technology-intensive environments [80].

From a practical perspective, the DBSN provides a useful tool for identifying risks associated with digital workload. It may support healthcare administrators and nurse managers in developing targeted interventions, such as improving system usability, reducing documentation burden, and strengthening organizational support. These implications are consistent with recent studies highlighting the effects of digital fatigue and occupational stress on nurses' job performance and well-being [84, 98]. Addressing digital workload at the organizational level may contribute to improving both nurse well-being and the quality of care.

Limitations

This study has several limitations. First, the data were collected from a single public hospital, which may limit the generalizability of the findings to different healthcare settings [105]. Second, data collection was based on an online survey, which may have favored participation by nurses who are more familiar with digital tools [106]. Third, due to the cross-sectional design, the observed relationships should not be interpreted as causal [107]. Finally, the use of self-reported data may introduce response bias [108]. In addition, organizational stress was included as an observed variable, which may not fully capture its multidimensional structure [109]. Future research should examine these relationships using longitudinal designs and alternative measurement approaches. These limitations should be considered when interpreting the findings, as they may influence the generalizability and strength of the observed relationships.

Future Research Directions

Future studies should examine the applicability of the Digital Burnout Scale in Nursing across different healthcare settings, institutions, and cultural contexts to enhance its generalizability. Testing the scale in diverse clinical environments, such as intensive care units, outpatient services, and various hospital types, would provide a more comprehensive understanding of digital burnout in nursing practice.

Beyond measurement, future research should focus on identifying strategies to reduce digital burnout. In particular, the design and usability of digital systems in nursing should be reconsidered. Simplifying system interfaces, reducing unnecessary data entry, and minimizing repetitive documentation could help alleviate digital workload and related strain. In addition, improving system integration and standardizing digital procedures across units may reduce inconsistencies that contribute to stress.

Another important direction is to involve nurses more actively in the design and improvement of digital systems. Approaches that incorporate user experience and frontline feedback are likely to produce more effective and sustainable solutions. Examining how such participatory approaches influence digital burnout would provide valuable insights for both system developers and healthcare managers.

Finally, longitudinal and intervention-based studies are needed to examine how these improvements influence digital burnout over time and to generate evidence-based recommendations for healthcare organizations.

5. CONCLUSION

This study developed and validated the Digital Burnout Scale in Nursing (DBSN) and assessed its association with organizational stress. The findings support a two-factor structure, Emotional Exhaustion and Erosion of Human Interaction. Evidence for construct validity and internal consistency was strong.

The relationship between digital burnout and organizational stress was also examined. The findings showed a positive association between these variables. This association was driven by erosion of human interaction. Emotional exhaustion did not show a significant effect. Changes in interpersonal interaction in digital care settings may therefore play a central role in explaining organizational stress.

The results further suggest that digital burnout reflects more than individual strain. Organizational conditions, digital workload, and system demands appear to shape this experience.

The DBSN provides a context-specific tool for assessing burnout related to digitalization in nursing. It may help identify areas of digital workload and support organizational improvements. Addressing these areas may support nurse well-being and help maintain the quality of care in digital healthcare settings.

Declarations

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Author's contributions

FNKŞ conceived and designed the study, developed the scale, collected the data, performed the statistical analyses, interpreted the results, and drafted and critically revised the manuscript. The author read and approved the final version of the manuscript.

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Data availability

The data supporting this study's results are available from the corresponding author upon reasonable request.

Ethics approval

Ethical approval for the study was granted by the Hatay Mustafa Kemal University Social and Human Sciences Scientific Research and Publication Ethics Committee at its meeting held on 05 December 2025, meeting number 14, with decision number 19. The study was conducted in accordance with the principles of the Declaration of Helsinki.

Consent to participate

Before starting the survey, participants were presented with an information text and a statement indicating voluntary participation. The questionnaire could be accessed only after participants confirmed their consent by selecting the relevant checkbox. Participation was voluntary, and confidentiality and anonymity were ensured.

Consent for publication

Not applicable.

Competing interests

The author declares no competing interests.

Clinical trial number

Not applicable.

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