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Re-examination of the digital burnout scale using second-order confirmatory factor analysis (CFA) and the digital burnout feature among pre-service teachers

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Abstract

This study aims to examine the digital burnout scale in pre-service teachers and describe the occurring digital burnout. The research respondents consist of 150 prospective teachers from the Faculty of Education out of 1328 students. Data were analysed using Confirmatory Factor Analysis (CFA) to test the digital burnout instrument and descriptive analysis to depict the patterns of digital burnout with three main indicators: digital aging, digital deprivation, and emotional exhaustion. The results of the CFA indicate that there are several questionnaire items with loading factors less than 0.50, specifically in the digital aging (DA11 and DA12) and emotional exhaustion (EX1, EX2, and EX6) sections. Therefore, these items were eliminated from the instrument. Descriptive analysis results show that 37% of pre-service teachers experience digital aging, 61% experience digital deprivation, and 20% experience emotional exhaustion. Overall, the digital burnout indicators reveal that 42% of pre-service teachers are undergoing digital burnout. These findings suggest that the massive and uncontrolled use of technology has proven to cause digital burnout. The study concludes that the used instrument is valid with the improvement of five questionnaire items that cannot be used with a standard factor loading of 0.5. Additionally, the research also concludes that 42% of pre-service teachers are experiencing digital burnout. Along with observing the aspect combination of digital technology and emotional aspects of prospective teachers, the utilization of technology in teacher professional growth will present positive results and avoid the digital burnout emergence in prospective teachers.

Keywords: Burnout, CFA, digital, pre-service teacher, technology

Introduction

The issue of teachers' social welfare (wellbeing) is a topic of discussion among experts in the world of education. Kingsford-Smith et al. (2023) explained that one of the factors that influences teacher wellbeing is the working conditions themselves. It was further explained that workload, student behaviour, and collaboration with colleagues have a direct influence on teacher wellbeing. The importance of emotional well-being needs to be given serious attention by stakeholders. The importance of wellbeing for teachers also includes prospective teachers (Mairitsch et al., 2021) with influencing factors, namely time management, work-life balance, relationships, finding purpose, and meaning, study program structure, as well as the status of teaching and certain languages in each society.

After the Covid 19 pandemic occurred, the use of digital media became very massive. Learning that is forced to use online mode and all other activities are also carried out online has given rise to a new habit that is full of digitalization. This raise concerns that excessive use of technology will have a negative impact. Therefore, this massive development of digitalization needs to be balanced with digital self-control (Monge Roffarello & De Russis, 2023) to avoid digital burnout (da Silva et al., 2024).

Burnout is a condition where a person no longer has the desire to develop themselves, is cynical about new things and lacks professionalism in doing work (Hakanen et al., 2006). The burnout experienced by a teacher makes it possible for him to teach only because he fulfils his obligations and is reluctant to develop new learning methods.

Burnout has a negative impact on a person's performance (Salami, 2011). At this stage a person will often experience stress from the routine work they do. As a teacher, the burnout you experience will directly impact students. Students will not get maximum service from teachers and ultimately students' understanding of a particular lesson will not be optimal. Several studies regarding burnout have been conducted. Burnout has a big impact on a person's performance (Shamsafrouz & Haghverdi, 2015). Apart from that, some teachers who feel dissatisfied with their work will experience burnout (Weaire, 2013). Burnout can arise due to several factors, namely work environment, academic load and promotion (Karabiyik et al., 2008).

With the current development of technology, especially after the Covid-19 pandemic, the number of internet users in Indonesia has increased very significantly. The average time spent using the internet is 12 hours for browsing, streaming, and using social media. This development also has an impact on the learning process in higher education where learning using online modes, both synchronous and asynchronous, has become a very familiar mode. Therefore, digital transformation after the pandemic needs to be considered (Soto-Acosta, 2024). Unfortunately, the increased use of the internet to the level of internet addiction is closely related to digital burnout (da Silva et al., 2024). In reality, work stress alone does not affect burnout without the massive use of digital media, (Kaltenegger et al., 2024) which then leads to technostress that is directly linked to digital burnout in prospective teachers. This also occurs at the worker level, where the extensive utilization of technology allows employees to work from anywhere. Unfortunately, this becomes a trigger for unpredictable working hours, which can increase stress, burnout, and even lead to higher levels of conflict within families. (Bullini Orlandi et al., 2024).

Excessive use of devices and the internet can cause digital burnout. Digital burnout, a feeling of anxiety, tiredness and apathy caused by spending too much time in front of digital devices, is an increasing problem. Potter et al. (2022) states that the use of digital communication at work has positive and negative impacts on workers, one of which is related to the well-being (mental well-being) of employees. The use of various digital media has empirically shown the impact of burnout on certain workers (Kelty et al., 2021) this is caused by digital overload (Bunjak et al., 2021). Therefore, digital burnout measurements need to be carried out.

One method of measuring digital burnout has been carried out by Erten & Özdemir (2020). There are three components that emerge, namely digital aging, digital deprivation, and emotional exhaustion. Measuring digital burnout also needs to be carried out on students, where currently every student has a device and sufficient internet connection as well as lecture activities that use various media such as learning management systems and so on. Therefore, this study aims to test the scale that has been developed in the context of student use Confirmatory Factor Analysis (CFA).

Conceptual framework

Digital burnout has emerged as a critical issue due to the increasing reliance on digital tools in education. Digital burnout is influenced by multiple factors, including excessive screen time (Pandya & Lodha, 2021), cognitive overload (Tafesse et al., 2024), and emotional exhaustion (Klusmann et al., 2023). Additionally, poor digital literacy and inefficient time management can exacerbate burnout, as individuals struggle to balance academic demands with personal well-being to enhance students' employability (Thelma et al., 2024).

Key components of the digital burnout include individual factors such as psychological resilience (Clark et al., 2023), self-regulation in technology use (Navarro et al., 2023), and perceived digital competence (Kumpikaitė-Valiūnienė, Aslan, Duobienė, Glińska, & Anandkumar, 2021). Environmental factors, namely institutional support (Graham et al., 2023), workload expectations (Taylor & Frechette, 2022), and the digital learning environment (Koivuneva & Ruokamo, 2022), further shape the experience of digital burnout. Moreover, a lack of structured breaks and ineffective coping strategies can intensify feelings of exhaustion and reduce productivity (Demerouti, 2023). Outcomes which consist of effects on motivation (Pham Thi & Duong, 2024), academic performance (Lluch et al., 2022), and mental well-being (Koivuneva & Ruokamo, 2022) highlight the significance of addressing these factors to create a more sustainable digital learning environment.

Digital burnout is further intensified by the blurring of boundaries between academic and personal life due to the constant availability of digital resources (Miller & Flint-Stipp, 2019). Many pre-service teachers struggle to establish a clear separation between study time and personal time, leading to prolonged exposure to digital screens and increased mental fatigue. This phenomenon is exacerbated by the expectation of immediate responsiveness to academic tasks, such as online discussions, digital assignments, and instant feedback loops (Anton & Van Ryzin, 2024). Without structured time management and self-imposed digital boundaries, pre-service teachers may experience difficulty disengaging from academic pressures, resulting in prolonged stress and reduced overall well-being. Moreover, the social aspect of digital engagement also plays a crucial role in digital burnout. While digital platforms provide opportunities for collaboration and interaction, excessive reliance on online peer discussions, virtual study groups, and social media for academic communication can lead to information overload and social fatigue. The pressure to stay constantly connected with peers and instructors through digital means may create a sense of obligation to be "always on", reducing the opportunity for mental rest and recovery. Additionally, the comparison culture fostered by social media, where students measure their academic progress and achievements against their peers, can contribute to feelings of inadequacy and anxiety, further increasing the risk of burnout. Addressing these challenges requires a holistic approach that includes institutional policies to promote healthy digital habits, digital well-being programs, and awareness campaigns aimed at educating pre-service teachers on the importance of balanced technology use in their academic and personal lives.

Research objectives

This study aims to:

1. examine the validity and reliability of the digital burnout instrument for pre-service teacher respondents, and
2. describe the level of digital burnout experienced by pre-service teachers.

Methodology

Research design

This research uses confirmatory factor analysis (CFA) and descriptive analysis to explain the pattern of digital burnout that occurs. Confirmatory factor analysis (CFA) is a part of structural equation modelling (SEM) with a specific purpose. CFA is a way to test how well a predetermined measurement theory consisting of measurable variables and factors corresponds to the reality captured by the data (Hair et al., 2020). Recommended cutoff loading factors vary from .40, .50, .60, or .70. This study used a cut-off of .50 and several criteria according to the model. Although there are agreed measures between statisticians, these criteria can differ from one reference to another because they can be subjective (Hair et al., 2020; Schumacker & Lomax, 2015).

This research is associative research with a Covariance-Based Structural Equation Modelling (CB-SEM) approach focusing on Confirmatory Factor Analysis. The research procedure consists of five SEM stages: (1) model development based on theory, (2) constructing the path diagram, (3) selecting the type of input matrix and estimating the proposed model (maximum likelihood), (4) identifying the structural model (with a minimum factor loading of .40), and (5) evaluating model fit based on goodness-of-fit criteria. Data analysis was conducted using maximum likelihood estimation with the following goodness-of-fit criteria:

Table 1

Goodness of Fit Criteria

Model-fit criterion	Acceptable level	Interpretation
Chi-square	Tabled value (χ^2)	Compares obtained $\chi 2$ value with tabled value for given *df* (can be obtained from AMOS)
Goodness-of-fit index (GFI)	0 (no fit) to 1 (perfect fit)	Value close to .90 or .95 reflects a good fit
Adjusted GFI	0 (no fit) to 1 (perfect fit)	Value adjusted for *df*, with .90 or .95 reflects a good fit
Root-mean square residual (RMR)	Researcher defines level	Indicates the closeness of Σ to S matrices
Standardized RMR (SRMR)	< .05	Value less than .05 indicates a good model fit
Root-mean-square error of approximation (RMSEA)	.05 to .08	Value of .05 to .08 indicates close fit
Tucker–Lewis Index (TLI)	0 (no fit) to 1 (perfect fit)	Value close to .90 or .95 reflects a good fit
Normed fit index (NFI)	0 (no fit) to 1 (perfect fit)	Value close to .90 or .95 reflects a good fit

continued

Parsimony fit index (PNFI)	0 (no fit) to 1 (perfect fit)	Compares values in alternative models

Table 1 describes the goodness-of-fit criteria in the structural equation model. Several model fit criteria are included, such as chi-square, GFI, RMSEA, and PNFI. The results of the structural equation analysis should consider the goodness-of-fit criteria, although not all indicators must necessarily reach the fit level. According to various literature sources, achieving at least one goodness-of-fit criterion in each category (absolute, incremental, and parsimonious) is generally sufficient to determine whether a model is fit or not.

Respondents of the study

The research involves 150 prospective teachers from Faculty of Teacher Training and Education (FKIP) Muhammadiyah University of Surakarta. The sample is conducted using a simple random sampling approach across 11 (eleven) study programs in this Faculty.

Respondent demographic data

This research was conducted on students at the Faculty of Teacher Training and Education, Muhammadiyah University of Surakarta with a total of 150 students as respondents.

Table 2

Respondent Demographic

No.	Study program	Respondents
1.	Accounting Education	10
2.	Education For Early Childhood Education Teachers	3
3.	Bahasa Indonesia Education	18
4.	English Education	25
5.	Biology Education	11
6.	Geography Education	5
7.	Elementary School Teacher Education	30
8.	Civic Education	6
9.	Mathematic Education	14
10.	Sport Education	14
11.	Teacher Professional Education	5
12.	Information And Technology Education	9

Table 2 presents the number of respondents for each study program. There are twelve study programs included in this survey, all of which belong to the Faculty of Teacher Training and Education. The Primary Education program has the highest number of respondents, followed by the Indonesian Language Education and English Language Education programs. Meanwhile, the program with the fewest respondents is the Early Childhood Teacher Education program.

Findings and discussions

Reliability analysis

The following are reliability analysis results on the instrument used.

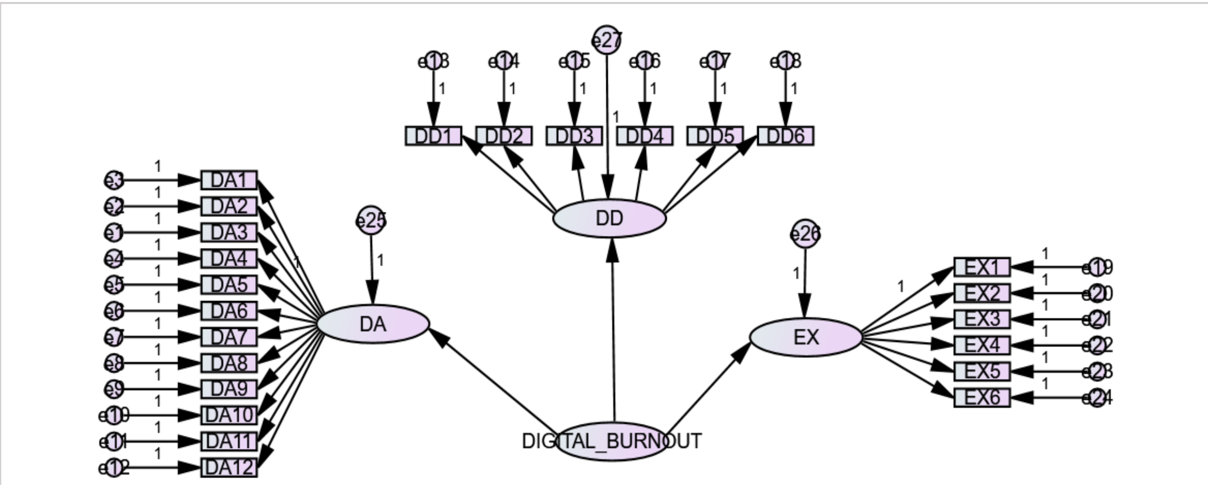
Reliability statistics result presents a developed instrument by Erten & Özdemir (2020) has reliability .88 in the context of student respondents who prospective teachers in Indonesia. The result presents the instrument can provide valid information about digital burnout which occurs by students of prospective teachers. The reliability value of 88.7% exceeds the minimum requirement of .60 or .07.

Confirmatory Factor Analysis (CFA)

Second-order CFA is a technique for interpreting a multilevel and multidimensional scale by conveying various dimensions under the rubric of a general higher-level factor. This analysis tests a construct which is indicated by several other constructs, some of which are unobserved variables. Figure 1 describes the digital burnout model discovered by Erten & Özdemir (2020). In this model, digital burnout is indicated by 3 factors, namely digital aging, digital deprivation, and emotional exhaustion. Digital aging is a condition experienced by adults related to the current use of digital technology which is shown by the impact of three components, namely ICT in everyday life, digital literacy of adults, and internet services and networks for adults (Yang & Lin, 2019). Digital deprivation is a socio-economic phenomenon that describes disparities in access and use of information and communication technology (ICT) between individuals, households, or geographic regions. (Kuc-Czarnecka, 2020). It was further explained that the meaning of digital deprivation continues to develop until it has three categories of meaning, namely binary Internet access (first level digital gap), digital skills (second level digital gap), and results of Internet use (third level digital gap). In the context of this research, the meaning of digital deprivation is more at level three, namely the digital gap as a result of internet use. Meanwhile, emotional exhaustion is a condition where a person experiences a decrease in energy, mental endurance and emotional skills as a result of chronic stress or excessive emotional burden.

Figure 1

Original Model of Digital Burnout



Note.
A *general note. This structural equation model (SEM) illustrates the relationship between Digital Aging (DA), Digital Deprivation (DD), Emotional Exhaustion (EX) in the context of Digital Burnout. Factor loadings greater than 0.50 are considered valid, while items below this threshold are eliminated. The numbers on the arrows indicate standardized factor loadings, showing the strength of the relationship between latent variables and their observed indicators. The numbers inside circles represent error variances for each observed variable. DA, DD, and EX serve as latent variables that contribute to Digital Burnout. he values 1.00 assigned to some paths indicate fixed reference points for model estimation.*

Table 3

Factor Loading Analysis Original Model

			Estimate	P	Factor Loading	Cut off	Justification
DA3	<---	DA	1,00		,61[a]	,50	Valid
DA2	<---	DA	,96	0,000	,52	,50	Valid
DA1	<---	DA	,94	0,000	,57	,50	Valid
DA4	<---	DA	1,04	0,000	,62	,50	Valid
DA5	<---	DA	1,02	0,000	,62	,50	Valid
DA6	<---	DA	1,26	0,000	,69	,50	Valid
DA7	<---	DA	1,22	0,000	,70	,50	Valid
DA8	<---	DA	1,20	0,000	,65	,50	Valid
DA9	<---	DA	,92	0,000	,57	,50	Valid
DA10	<---	DA	,78	0,000	,50	,50	Valid
DA11	<---	DA	,77	0,000	,48[b]	,50	Eliminated
DA12	<---	DA	,69	0,000	,42[c]	,50	Eliminated

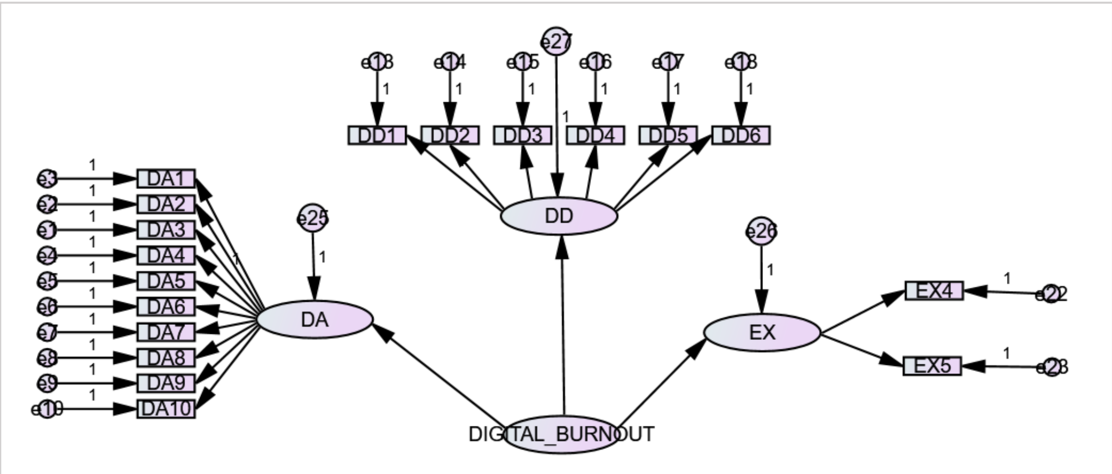
continued

DD1	<---	DD	1,00		,76[d]	,50	Valid
DD2	<---	DD	,83	0,000	,68	,50	Valid
DD3	<---	DD	1,09	0,000	,80	,50	Valid
DD4	<---	DD	1,05	0,000	,72	,50	Valid
DD5	<---	DD	1,04	0,000	,74	,50	Valid
DD6	<---	DD	,90	0,000	,71	,50	Valid
EX1	<---	EX	1,00		,40[e]	,50	Eliminated
EX2	<---	EX	1,13	0,000	,49[f]	,50	Eliminated
EX3	<---	EX	1,09	0,000	,48[f]	,50	Eliminated
EX4	<---	EX	1,96	0,000	,88	,50	Valid
EX5	<---	EX	1,84	0,000	,82	,50	Valid
EX6	<---	EX	,98	0,000	,42[e]	,50	Eliminated

General Note. Factor loadings greater than 0.50 are considered valid. Items with values below 0.50 are eliminated. DA = Digital Adaptation; DD = Digital Demands; EX = Exhaustion.
***a** DA3 was used as a reference with a fixed factor loading of 1.00.*
***b** DA11 had a factor loading below the cut-off and was therefore eliminated.*
***c** DA12 did not meet the minimum factor loading criterion.*
***d** DD1 was used as a reference in the confirmatory model.*
***e** EX1 and EX6 had factor loadings that were too low to be retained.*
***f** EX2 and EX3 fell below the validity threshold and were therefore eliminated.*

Figure 2

Digital Burnout Model Revision



Note.
General note. This structural equation model (SEM) represents the relationship between Digital Aging (DA), Digital Deprivation (DD), and Emotional Exhaustion (EX) in the context of Digital Burnout after item refinement. Factor loadings greater than 0.50 are considered valid, while items below this threshold have been eliminated. The numbers on the arrows represent standardized factor loadings, indicating the strength of the relationship between latent variables and their observed indicators. The numbers inside circles denote error variances for each observed variable. DA, DD, and EX act as latent variables contributing to Digital Burnout. The values 1.00 assigned to some paths serve as fixed reference points for model estimation. Compared to the previous model, items EX1, EX2, EX3, DA11, and DA12 have been removed, as they did not meet the factor loading criteria.

Table 4

Factor Loading Analysis Revised Model

			Estimate	P	Factor Loading	Cut off	Justification
DA2	<---	DA	,94	,000	,63	,50	Valid
DA1	<---	DA	,91	,000	,52	,50	Valid
DA4	<---	DA	1,05	,000	,57	,50	Valid
DA5	<---	DA	1,00[a]	,000	,65	,50	Valid
DA6	<---	DA	1,28	,000	,63	,50	Valid
DA7	<---	DA	1,17	,000	,72	,50	Valid
DA8	<---	DA	1,14	,000	,69	,50	Valid
DA9	<---	DA	,88	,000	,64	,50	Valid
DA10	<---	DA	,71	,000	,55	,50	Valid

continued

DD1	<---	DD	1,00		,46[b]	,50	Eliminated
DD2	<---	DD	,83	,000	,76[c]	,50	Valid
DD3	<---	DD	1,09	,000	,68[c]	,50	Valid
DD4	<---	DD	1,05	,000	,80[c]	,50	Valid
DD5	<---	DD	1,04	,000	,72[c]	,50	Valid
DD6	<---	DD	,90	,000	,74[c]	,50	Valid
EX4	<---	EX	,64	,000	,71[d]	,50	Valid
EX5	<---	EX	,53	,000	,86[d]	,50	Valid

Note. A general note Factor loadings greater than 0.50 are considered valid, while items below this threshold are eliminated. DA = Digital Aging; DD = Digital Deprivation; EX = Emotional Exhaustion.
a DA5 was used as a reference with a fixed factor loading of 1.00.
b DD1 had a factor loading below the cut-off and was therefore eliminated.
c DD2 to DD6 met the validity threshold and were retained in the model.
d EX4 and EX5 had strong factor loadings and were retained as valid indicators.

According to the results of the factor loading analysis, it shows that digital aging can be demonstrated using 9 question items, digital deprivation with 6 questions and emotional exhaustion can be explained using two manifest items. Testing this model needs to be carried out further by analysing the fit model with three criteria, namely absolute, incremental, and parsimonious fit indices. In this model fit analysis, the expected result is that not all fit models meet the criteria, but there is at least one fit measure for each criterion that meets the requirements.

Table 6

Absolute Fit Indices Result of Second-Order CFA Digital Burnout

No	Fit measure	Good fit	Acceptable fit	Result	Interpretation
1.	Chi-Square	x^2 is low relative to df with insignificant p-value (p > .05)	x^2 is low relative to df with insignificant p-value (p > .05)	315,107[a]	Not fit (Very sensitive with sample number)
2.	GFI	≥ .95	Close to .90	,81[b]	Acceptable fit
3.	RMSEA	≤ .05	≤ .08	,08[c]	Acceptable fit
4.	RMR	Small Value	Small Value	,07[d]	Acceptable fit

Note.
A ***general note*** This table presents the model fit indices used to evaluate the structural equation model. The criteria for Good Fit and Acceptable Fit are provided for comparison with the actual results.

a. Chi-Square (χ^2): The model's chi-square value is 315.107, which suggests a poor fit, as it is highly sensitive to sample size.
b. GFI (Goodness-of-Fit Index): The value of 0.81 falls within the acceptable range, indicating a moderate model fit.
c. RMSEA (Root Mean Square Error of Approximation): The value of 0.08 suggests an acceptable fit, meaning the model reasonably approximates the population covariance.
d. RMR (Root Mean Square Residual): The value of 0.07 is within the acceptable threshold, suggesting that residual differences between observed and predicted values are within a reasonable range.

Overall, the model demonstrates an acceptable fit, despite the chi-square test indicating a poor fit due to its sensitivity to sample size.

Table 7

Incremental Fit Indices Result of Second-Order

No	Fit measure	Good fit	Acceptable fit	Result	Interpretation
1.	TLI	≥ .90	Close to .90	0.83	Acceptable fit
2.	NFI	≥ .95	Close to .90	0.76	Acceptable fit
3.	IFI	≥ .90	> .8	0.86	Acceptable fit
4.	RFI	≥ .90	> .8	0.73	Not Fit
5.	CFI	≥ .97	≥ .80	0.85	Acceptable fit

Note.
A general note. *This table presents the model fit indices used to assess the overall fit of the structural equation model (SEM). The criteria for Good Fit and Acceptable Fit are provided for comparison with the actual results.*

a. *TLI (Tucker-Lewis Index): The value of 0.83 falls within the acceptable range, indicating a moderately fitting model.*
b. *NFI (Normed Fit Index): The value of 0.76 is below the commonly accepted threshold of 0.90, suggesting room for model improvement.*
c. *IFI (Incremental Fit Index): The value of 0.86 meets the acceptable fit criteria, showing that the model explains a reasonable proportion of variance.*
d. *RFI (Relative Fit Index): The value of 0.73 is lower than the ideal ≥ 0.90 but is still within the acceptable range (> 0.80), indicating that the model requires some refinement.*
e. *CFI (Comparative Fit Index): With a value of 0.85, the model achieves an acceptable fit, though it does not meet the ideal threshold of ≥ 0.97.*

The model achieves an acceptable fit but does not reach a good fit across all indices. Some refinements may be needed to improve the model's overall fit.

Table 8

Parsimonious Fit Indices

No	Fit measure	Good fit	Acceptable fit	Result	Interpretation
1.	AGFI	≥ .90	≥ .85	0.76	Acceptable fit
2.	PNFI	≥ .60	≥ .50	0.66	Good fit
3.	PCFI	≥ .60	≥ .50	0.74	Good fit
4.	PGFI	≥ .60	≥ .50	0.63	Good fit

Note.
A general note. This table presents the model fit indices used to evaluate the structural equation model (SEM). The criteria for Good Fit and Acceptable Fit are provided for comparison with the actual results.

a. *AGFI (Adjusted Goodness-of-Fit Index): The value of 0.760 falls within the acceptable range (≥ 0.85) but does not meet the good fit threshold (≥ 0.90). AGFI ranges from 0 (not fit) to 1 (perfect fit).*
b. *PNFI (Parsimonious Normed Fit Index): The value of 0.667 exceeds the ≥ 0.60 threshold, indicating a good fit for the model.*
c. *PCFI (Parsimonious Comparative Fit Index): With a value of 0.748, the model meets the good fit criteria, suggesting an efficient balance between model complexity and fit.*
d. *PGFI (Parsimonious Goodness-of-Fit Index): The value of 0.636 meets the good fit threshold (≥ 0.60), indicating an acceptable model fit with an appropriate level of parsimony.*

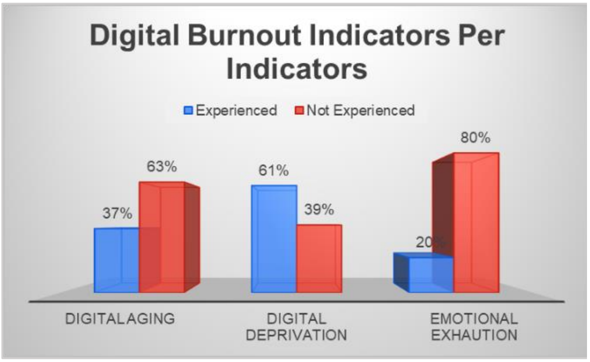
The model achieves a good fit based on PNFI, PCFI, and PGFI but only an acceptable fit based on AGFI. Further model refinement may improve the AGFI score to enhance overall model adequacy.

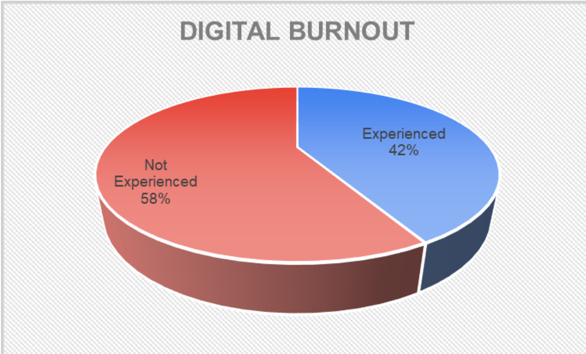
Description of digital burnout data from the revised instrument

Based on the results of the confirmatory factor analysis, the instrument that has been tested is used to describe the digital burnout that occurs in respondents. The description is divided into two, namely a description based on indicators and score regarding digital burnout.

Figure 3

Digital Burnout Descriptions





Note.
A **general note.** *The first chart illustrates the proportion of individuals experiencing different indicators of digital burnout, categorized into Digital Aging, Digital Deprivation, and Emotional Exhaustion. The data reveals that Emotional Exhaustion is the most prevalent, with 80% reporting its effects, while Digital Deprivation shows a more balanced distribution (61% experienced vs. 39% not experienced). Digital Aging is the least experienced, affecting 37% of respondents. The second chart provides an overall view of digital burnout prevalence. It shows that 42% of individuals report experiencing digital burnout, while 58% do not. These findings highlight the significant presence of digital burnout, with Emotional Exhaustion being the most prominent indicator.*

Figure 3 describes the percentage of respondents who experience digital aging, digital deprivation, and emotional exhaustion. In general, most respondents experienced digital deprivation. This means that the current massive use of the internet has produced an undesirable impact for the majority of the respondents. As stated before, there are three categories of deprivation meaning, namely binary Internet access (first level digital gap), digital skills (second level digital gap), and results of Internet use (third level digital gap). Unfortunately, this research has not described yet in detail digital deprivation in those three levels of meaning. Nevertheless, the results have shown that there is a disparity in the use of the internet among the respondents. When looking at the constructed questionnaire, there are several questions about deprivation that respondents feel uncomfortable with if they do not have access to the internet or when their device is offline. They also think about new messages, feel something is missing when they do not have their devices and so on. These results indicate an extraordinary dependence on the digital devices owned. The disparity in internet usage (digital devices) in the context of this research certainly indicates that the broad purpose of digital access has had much deeper impact than what should have occurred. Currently, individuals tend to find it more challenging to leave their digital access when interacting with other aspects of their lives.

Even so, only 37% of respondents stated that the use of various digital devices currently interferes with their normal lives. Digital aging is a condition experienced by adults related to the current use of digital technology which is shown by the impact of three components, namely ICT in everyday life, digital literacy of adults, and internet services and networks for adults. In the context of this research, digital aging refers to the impact of technology usage in everyday social life. Examining the tested questions, such as a decrease in productivity after using digital devices, constant feelings of tiredness, stress, and so on, the questionnaire delves more into the negative effects on the social life of the community from the use of digital devices. The results indicate that 37% of the respondents feel negative impacts from the use of information and communication technology (ICT). This suggests a significant portion of the respondents is capable of exercising self-control in their use of digital access.

Interestingly, there are only 20% of respondents who feel emotional exhaustion. Emotional exhaustion is a condition when a person experiences a decrease in energy, mental endurance and emotional skills as a result of chronic stress or excessive emotional burden. It appears that a majority of the respondents (80%) are able to control their emotions even though they use the internet throughout their time. This is a positive indication that their self-control abilities can overcome various negative impacts that may arise from the use of digital access. In fact, the development of digital-based technology has been able to enhance various sectors of life, emphasising the need for technology to be utilized and mastered.

Student wellbeing is an important factor that must be considered in learning. Pre-service student currently (2024) is a generation that is living a life full of digitalization in various fields such as lectures and daily social life. This means that the use of devices to access digital content is unavoidable and has become a real necessity. Moreover, Fergi Diarta et al. (2021) stated that one of the uses of digital media, namely digital books, is highly effective in enhancing the motivation of learners in their studies. Therefore, identifying the condition of digital burnout in pre-service students is important to prepare pre-service teachers who are able to control the use of digital media proportionally.

The research results showed that almost half of the respondents felt digital burnout using instruments that had been tested again, showing an imbalance in using digital platforms in everyday life. This digitalization process has touched various levels of society, including people in rural areas (Fikri Zul Fahmi & Ivanie Destila Sari, 2020). The use of various digital platforms has been proven to influence a person's behaviour and motivation (Ueno et al., 2023). The influence on behaviour is also evident in the context of learning. Arif Rahman Hakim et al., (2023) concluded that the use of digital media, particularly literature-based learning videos, can enhance the literacy skills of the participants in education. In general, digital literacy can help the reading interest in students (Arif Rahman Hakim et al., 2023).

Digital use in everyday life can change a person's behaviour (Hawkes et al., 2023). In addition to the undeniable benefits of using digital media, there are certainly aspects that need attention. For example, Surya Jatmika et al. (2022) states that there is a tendency for many students to engage in cheating when using digital media in learning. Individuals exhibited digital burnout levels higher than the average, influenced by factors such as the daily duration of online activities, stress levels, overall physical and mental well-being, and economic status (Durmuş et al., 2022). This also proves that high levels of digital work can trigger stress and burnout among workers (Kaltenegger et al., 2023).

The condition of digital burnout, which is divided into three indicators, namely digital aging, digital deprivation, and emotional exhaustion, needs to be managed in such a way so it does not accumulate into digital burnout which has a negative impact on the behaviour and motivation of pre-service teachers. Hence, avoiding burnout in digital era is necessary (Kelty et al., 2021) because in the case of high technology overload, cognitive absorption with technology leads to burnout and reduces creativity levels of the workers (Bunjak et al., 2021).

Last but not least, digital technology is an important resource to support human life today, including teacher professional growth. Overuse of digital technology can have negative impacts on pre-service teachers. By considering the balance between the ease of digital technology and the emotional well-being of pre-service teachers, the use of technology in teacher professional growth can have highly positive effects and help prevent digital burnout among pre-service teachers.

Conclusions and recommendations

The findings of this study highlight that digital burnout is a significant issue among pre-service teachers, affecting their motivation, behavior, and overall well-being. The instrument of the digital burnout is valid with some revisions in the context of pre-service teachers as objects. While digital media provides numerous benefits, such as enhancing learning motivation and literacy skills, excessive use leads to digital aging, digital deprivation, and emotional exhaustion. This imbalance can negatively impact pre-service teachers' creativity and professional growth. Given the importance of digital technology in education, it is crucial to manage digital media usage proportionally to maintain both productivity and emotional well-being. The universities may implement some policies to prevent digital burnout such as digital well-being education, balanced digital integration in learning, mental health support, Self-Regulation Strategies for Pre-Service Teachers, and Institutional Policies for Healthy Digital Practices. By implementing these strategies, pre-service teachers can harness the benefits of digital technology while mitigating the risks of digital burnout, ultimately fostering a healthier and more effective teaching profession.

Conflict of interest

I declare no conflicts of interest. I have not received any financial or non-financial support or services from any third parties. There are no relationships or affiliations that could be perceived as influencing this manuscript. I affirm that the work was conducted independently and that all opinions expressed are my own

Author contribution

1. Muhammad Fahmi Johan Syah: Main Contributor (Proposal, Data Analysis, Manuscript Writing)
2. Amanda Putri Ardani: Co-Contributor (Data collection, Data Analysis)
3. Briliansa Rama Luthfi: Co-Contributor (Data collection, Data Analysis)

Data availability statement

Data will be made available on request.

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