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THE IMPACT OF DIGITAL ADDICTION ON TECHNOLOGY-RELATED FATIGUE AMONG UNIVERSITY PRESERVICE TEACHERS IN GHANA

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ABSTRACT

In digitally connected environments, users of digital technologies and applications need to pay persistent attention to the overwhelming demands of their use. These expanded energy conditions may induce technology-related fatigue, leading to a physical and mental imbalance in the availability of the inner resources needed to perform certain tasks. In this study, we analysed the effects of subtypes of digital addiction (smartphone addiction, social media addiction, internet gaming disorder, and problematic internet use) on technology-related fatigue among university preservice teachers in Ghana. Employing a descriptive correlational design, data were collected from 220 preservice teachers at a public university in Ghana. Data were garnered employing the sociodemographic traits, psychometric scales that measure the subtypes of digital addiction and the Piper Fatigue Scale. Bivariate correlation (Pearson's r) and multivariate regression analysis were used to analyse the relationship between the digital addiction subtypes and technology-related fatigue. The results illustrated that the subtypes of digital addiction explained 27.9% (R^2 = 0.279) of the total variance in fatigue levels. Smartphone addiction was the most important factor associated with technology-related fatigue. Notably, this study is among the first to empirically establish a statistically significant relationship between digital addiction subtypes and TRF in the context of higher education in Sub-Saharan Africa. The findings underscore the need for awareness campaigns and targeted interventions within teacher education programmes to mitigate the adverse health impacts of digital overuse.

Keywords: Digital addiction, Technology fatigue, Preservice teachers, Digitally-connected devices, Internet apps, Ghana.

INTRODUCTION

The increasing integration of technology into daily life has led to a significant increase in the use of digital devices such as smartphones, laptops, and tablets (Çalhan & Göksu, 2024; Tülübaş *et al.*, 2023; Essel *et al.*,2022a; Essel *et al.*, 2018; Almourad *et al.*, 2020). While these devices have greatly improved communication, accessibility to information, and made many tasks more convenient, overuse of these devices has been linked to a phenomenon known as digital addiction (Tachie-Menson *et al.*, 2025; Cemiloglu *et al.*, 2022; Meng *et al.*, 2022). Digital addiction (DA) is defined as excessive use of digital devices that leads to negative impacts on an individual's physical, mental, and social well-being (Lam & Harcourt, 2024; Seema *et al.*, 2023; Çimke et al, 2023; Christakis, 2019; Sert *et al.*, 2019). As representative sets of subtypes of DA at a global level, Meng *et al.* (2022) assert that DA manifests in various forms, including smartphone addiction (SA), social media addiction (SMA), internet gaming disorder (IGD), and problematic internet use (PIU). Besides, DA as an umbrella term includes subtypes of the long-established issue of the profoundlydebated subject of game addiction, problematic internet use, and the emerging subject of problematic social media use or different digital media addiction (Christakis, 2019). Notwithstanding, DA does not necessarily involve Internet use and addiction to online activities, but also dependence on offline activities using digital devices and apps (e.g., addiction to offline games) (Genc *et al.*, 2024; Almourad *et al.*, 2020; Christakis, 2019). These forms of digital addiction have their own unique characteristics, but all of them have the potential to lead to negative consequences on an individual's life (Small *et al.*, 2022). Accordingly, this study conceptualises DA as a pattern of compulsive, unregulated and impulsive use of digitally-connected devices and apps, with or without active internet connectivity, which leads to adverse effects (Almourad *et al.*, 2020; Alrobai *et al.*, 2019; Ali *et al.*, 2015) not explained by other disorders (O'Brien *et al.*, 2022; Kuss & Pontes, 2019). Cemiloglu *et al.* (2022) also highlighted the importance of addressing digital addiction as it is becoming an increasing public health concern, with a meta-analysis by Meng *et al.* (2022) reporting a global prevalence of DA in the general population to be around 5%.

In the educational ecosystem, the use of digitally-connected devices and apps has become an integral part of the learning process. University students, including preservice teachers, are frequently required to use digital devices in their academic and personal lives (Essel *et al.*,2022a; Essel *et al.*,2022b; Essel *et al.*,2021a; Essel *et al.*,2021b; Sert *et al.*, 2019). Ghana and Sub-Saharan Africa have seen a sharp increase in the penetration of digital devices over the past decade. Furthermore, the COVID-19 pandemic has changed the way preservice teachers access and utilise digital devices and apps in public universities and colleges of education (Essel *et al.*, 2021a). Additionally, concern has been raised regarding increased risks of digital addiction during the COVID-19 pandemic (Király *et al.*, 2020) and post-pandemic conditions (Essel *et al.*, 2022a). These vulnerabilities could lead to significant impairments in health, study, work, and other social functions, as well as significant distress in personal, family, and social well-being (Dahl & Bergmark, 2020; Bell *et al.*, 2015; WHO, 2014). Moreover, Ghana falls within the lower-middle income or World Bank low region; thus, digital media is more likely to be used by individuals with economic or social disadvantages to manage stress, build connections, and ameliorate moods to escape unsatisfying external conditions which may lead to a relatively high prevalence of DA (Meng *et al.*, 2022; Lopez-Fernandez, 2018; Jang *et al.*, 2012). Notwithstanding, despite the widespread use of digitally-connected devices and apps among university students, little is known about the specific impact of DA on technology-related fatigue among preservice teachers in Ghana. As Christakis (2019) pointed out, there are still challenges in defining and studying DA in the context of education. Ong and Tan (2014) highlighted the importance of understanding DA in young people, as it is a growing concern among this population.

Although technology-related fatigue is a significant problem, few systematic studies have addressed it (Essel *et al.*, 2021a; Lee *et al.*, 2016; Ravindran *et al.*, 2014; Çoklar& Sahin, 2011). Shen *et al.* (2006) described Fatigue as a complex of mental and physical manifestations depicted by an overwhelming lack of energy, a sense of tiredness, and exhaustion linked with incapacitated physical or cognitive functioning. Technology-related fatigue (TRF) is a phenomenon that occurs as a result of prolonged use of digital devices and is characterised by symptoms such as fatigue, reduced motivation, and decreased productivity (Essel et 2021a; Dol, 2016; Lee *et al.*, 2016; Ong & Tan, 2014; Ravindran *et al.*, 2014). Studies have reported that individuals who are addicted to digital devices tend to experience higher levels of technology-related fatigue compared to non-addicted individuals (Meng *et al.*, 2022; Cemiloglu *et al.*, 2022; Almourad *et al.*, 2020; Christakis, 2019). Essel *et al.* (2021a) found that technology-induced stress among higher education students in Ghana was associated with reduced academic achievement and productivity, while Dol (2016) found a link between internet usage and fatigue and pain among university students. Besides, Multiple studies (Liang *et al.*, 2022; Borhany *et al.*, 2018; Yang *et al.*, 2017; Hellström *et al.*, 2015; Ayanniyi *et al.*, 2010) have also discovered a correlation between digitally-connected devices and musculoskeletal pain. However, the relationship between DA and TRF has not been well studied among university preservice teachers in Ghana, particularly considering the different forms of digital addiction such as SA, SMA, IGD, and PIU. In a unique contribution to literature, more is required to know about the potentially harmful impact of DA on preservice teachers' TRF levels in the Sub-Saharan region, specifically Ghana. Measuring DA and TRF will help assess, diagnose, and treat different symptoms among preservice teachers in Ghana. This study is novel as an extension of the previous emerging literature on DA and TRF.

Purpose and research questions

The current study is a descriptive correlational design and investigates preservice teachers' reported experience with digital-connected devices and internet apps using the results of psychometric measures on DA subtypes (i.e., SAS, smartphone addiction; IGD, internet gaming disorder; SMA, social media addiction; PIU, problematic internet use) as well as results from psychometric measures on Technology-Related Fatigue (i.e., PFS, Piper Fatigue Scale). Additionally, this study pinpoints the influence of the subtypes of DA, which are most significant on fatigue. To address the gaps identified, this study answers the following questions:

1. Is there a relationship between digital addiction subtypes and technology-related fatigue?
2. Do digital addiction subtypes explain student technology-related fatigue?

The other parts of the article are organised as follows: Section 2 focuses on the review of related literature concerning the predictors and dependent factors. Section 3 emphasises the methodological processes used for this study. Section 4 shows the results of this current study, analysed with descriptive (means, standard deviations, skewness and kurtosis) and inferential statistics (Independent T-test and Pearson correlation). Section 5 showed the garnered data and the results. Section 6 focuses on the discussion of the results, and section 7 finally, the conclusion, limitations and implications for further studies.

LITERATURE REVIEW

While digital technologies and applications make life more leisurely and contribute thoroughly to social modernisation and development, it has also ushered in the emergence of unexplored behavioural concerns, such as digital addiction, which is indicated by disproportionate use to the point of obsession and neglect of responsibilities (Sert *et al.*, 2019; Muslu & Bolşk, 2009). The term fatigue refers to a subjective state caused by an imbalance in the availability of the inner resources needed to perform physical or mental tasks (Yang & Wu, 2005). According to Piper *et al.* (1998), fatigue is defined as “a multidimensional experience that includes feelings of physical, emotional, and cognitive tiredness or exhaustion.” According to Shen *et al.* (2006), fatigue is a combination of mental and physical symptoms that include a severe loss of energy, a sense of tiredness, exhaustion, and impaired cognitive and physical function. Besides, fatigue can be deemed a mental situation where a protracted cognitive activity produces decreased performance (Mizuno *et al.*, 2011) and a physical situation as it correlates to an inability to perform a physical activity best (Hagberg, 1981). In this study, fatigue refers to a subjective estimate of a person’s boredom, tiredness, or burnout level from digital technology use. Piper *et al.* (1998) conceptualised fatigue as comprising four facets: Behavioural/Intensity fatigue, affective fatigue, sensory fatigue, and cognitive/Mental fatigue. The Behavioural/Intensity dimension assesses the intensity level of fatigue-related behaviour and the impact of fatigue on daily activities, which includes the level of fatigue during the day, the ability to perform daily activities, and the need to rest during the day (Piper *et al.*, 1998; Sert *et al.*, 2019). The Affective dimension assesses the emotional impact of fatigue on an individual, which includes feelings of exhaustion, irritability, and depression related to fatigue (Piper *et al.*, 1998; Sert *et al.*, 2019). The Sensory dimension assesses the mental, physical, and emotional sensations associated with fatigue, which include questions about muscle weakness, heaviness, and pain related to fatigue (Piper *et al.*, 1998; Sert *et al.*, 2019). The Cognitive/Mental dimension assesses the cognitive and mental effects of fatigue, including difficulty concentrating, memory problems, and fatigue-related confusion (Piper *et al.*, 1998; Sert *et al.*, 2019). Research on fatigue related to digital technologies is lacking, despite its widespread association with health issues and the use of information and communication technologies. Even though fatigue is a suboptimal health situation between disease and health (Xue *et al.*, 2012), prior research has shown that long-term fatigue is linked to not only low quality of life and decreased productivity at work (Sadeghniiat-Haghighi & Yazdi, 2015), but also to stroke-related cessation and ischemic heart condition (Pega *et al.*, 2021). Therefore, determining the causes of technology-related fatigue is critical for developing a successful deterrence procedure.

Regarding PIU, students exhibiting no PIU symptoms scored lower fatigue levels than students exhibiting higher levels of fatigue (Sert *et al.*, 2019; Bachleda & Darhiri, 2018). Liang *et al.* (2022) illustrated that PIU positively affects fatigue risk among students in a Chinese college. Lin *et al.* (2013) and Dol (2016) demonstrated that PIU plays an important role in fatigue. Bachleda and Darhiri (2018) indicated that students with PIU have significantly higher physical and mental fatigue levels than those without PIU. A Korean study (Kim *et al.*, 2010) also discovered a significant link between PIU, fatigue symptoms, sleep disturbances, and fast-food consumption. Besides, Borhany *et al.* (2018) discovered a significant relationship between the frequency of internet use and musculoskeletal problems. Moreover, studies that investigated the relationship between PIU, fatigue and sleep-related problems found that PIU positively correlated with fatigue symptoms (Liang *et al.*, 2022; Bener *et al.*, 2019; Bener *et al.*, 2016). IGD is characterised by excessive and problematic gaming behaviour that leads to negative impacts on an individual's physical, mental, and social well-being. The excessive use of digital devices, including gaming, has also been linked to fatigue. Concerning IGD, a study established a link to excessive fatigue, indicating that IGD might raise daytime fatigue (Ohayon & Roberts, 2021; Choi *et al.*, 2009). Männikkö *et al.* (2015) and Mentzoni *et al.* (2011) discovered that addictive game behaviour is linked negatively to psychophysical health measures such as fatigue. Similarly, several studies (Hellström *et al.*, 2015; Lui *et al.*, 2011) discovered that lengthened exposure to the digital game was linked with musculoskeletal symptoms. Chen *et al.* (2021) discovered that cyberloafing and perceived stress among college students were related to fatigue and negative coping styles, and discovered that the more significant the perceived stress, the greater the odds of fatigue and adverse coping styles related to greater cyberloafing behaviour. Laato *et al.* (2022) studied the effect of location-based games on psychological well-being and found that playing location-based games, such as Pokemon GO, is associated with improved psychological well-being, and suggests that location-based games can be used as a mechanism for reducing fatigue and fostering well-being. The literature suggests that excessive internet gaming is associated with increased fatigue levels. Studies have also found that interventions to reduce gaming addiction can positively reduce fatigue and improve psychological well-being (Afriwilda, 2021). However, it is essential to note that more study is needed to comprehend the mechanisms by which internet gaming and fatigue are related.

Due to fatigue with social media, a rising percentage of social media users are discontinuing their platform use (Dhir *et al.*, 2018; Guest Post, 2017). Social media users who experience fatigue are said to be mentally exhausted as a result of the technological, informational, and communicative excesses they encounter while participating in and interacting with various online social media outlets (Zhang *et al.*, 2016; Lee *et al.*, 2016; Bright *et al.*, 2015; Ravindran *et al.*, 2014). Prior literature reported that obsessive use of social media positively predicted the disposition to experience fatigue (Hattingh *et al.*, 2022; Tandon *et al.*, 2021a; Tandon *et al.*, 2021b; Dhir *et al.*, 2018). Other literature on new media usage indicates that disproportionate use of digital devices and maladaptive behaviour of social media results in emotional fatigue and exhaustion (Dhir *et al.*, 2018; Oberst *et al.*, 2017; Elhai *et al.*, 2016; Brand *et al.*, 2016; Ho *et al.*, 2014; Lin *et al.*, 2013). Scholars (Shin & Shin, 2016; Oghuma *et al.*, 2016) contend that fatigue with social media has substantial adverse implications for users. Moreover, social media use causes adverse emotions such as a dearth of energy, fatigue, and stress (Ballerini *et al.*, 2022; Ravindran *et al.*, 2014; Maier *et al.*, 2012). Compared to the extensive literature on obsessive use behaviour, scholars have only recently examined the precursors and outcomes of obsessive use of diverse new media forms (Dhir *et al.*, 2018). This study suggests that obsessive social media use may link with cognitive abilities and lead to fatigue with social media. Finally, excessive use of smartphones may contribute to feelings of mental and physical fatigue (Lekkas *et al.*, 2022). In response to fatigue and boredom, a study found that people interact more often with their smartphones as fatigue and boredom increases (Dora *et al.*, 2021; Whelan *et al.*, 2020). Overuse of smartphones can lead to musculoskeletal and visual impairments and interpersonal aptitudes (Priya & Subramaniyam, 2020). In a separate study (Khan, 2008) involving medical students in Saudi Arabia, one-fourth of students report fatigue experience from smartphone use. Sert *et al.* (2019) discovered an adverse influence of SA on all fatigue constructs (affective, behavioural, cognitive, and sensory). Moreover, in typical adults, Kim and Koo (2016) and Lee *et al.* (2017) underlined that continuous use of smartphones increases forward head posture, exacerbating fatigue in the shoulders and neck based on the span of smartphone use. Furthermore, exposure to smartphone apps has been connected to mental fatigue in decision-making abilities (Gantois *et al.*, 2020). These results indicate that additional study is necessary to determine the predictors and effects of TRF due to the excessive use of digitally-connected devices and apps. Based on the prior literature above, we aim to contribute to this extant knowledge by analysing the associations between DA and TRF.

MATERIALS AND METHODS

Design and sample

The current study employed a descriptive correlational study with a web data-gathering method. Preservice teachers were recruited by convenience sampling method in the current study. The preservice teachers were n = 220 samples, with 115 (52.3%) females and 105(47.7%) males in the Faculty of Educational Studies of a public university in Ghana. The preservice teachers' ages varied from 18 to 24 years, with a mean of 21.9 years (SD = 3.61 years). Male samples had a mean age of 22.44 years (SD = 4.11 years), and female samples had a mean age of 22.15 years (SD = 3.09 years).

Procedure and ethics

Emails were delivered via the university email accounts of the selected preservice teachers. All preservice teachers were older than or equal to 18 years old (Mohammed & Essel, 2018) and had at least one social media account (such as WhatsApp, Facebook, Twitter, Facetime, and other social media platforms). A link to the e-survey (Essel *et al.*, 2022a) powered by Google Forms was included in the email, as well as details about the study. It was made known to all preservice teachers prior to the distribution of the questionnaires that the collected data would only be utilised for scientific studies; they were not coerced to partake; their responses were anonymous; they could withdraw at any time, and it would not affect their performance on the final examination. Thus, the recruited preservice teachers had to provide informed consent electronically to partake in the study. The e-survey included items on sociodemographics, internet usage, and validated psychometric scales, which contained 74 items and required roughly 25 minutes to finish.

Moreover, every e-survey measure contains a trap question to guarantee that respondents read the questions without simply skimming through them. For example, BSMAS contained the following trap question: Choose "Strongly Agree" for this point. Even though this trap question is simple to answer correctly, it is highly unlikely that a speeder will recognize it. All of the sampled preservice teachers answered the trap item accurately. The College of Humanities and Social Sciences Ethics Committee authorised the current study in conformity with the

Declaration of Helsinki. Lastly, preservice teachers who were volitional to partake in the current study received an e-survey link after obtaining informed consent from their supervisors and instructors.

Measurements

Sociodemographic Profile:

A sociodemographic profile of the participants was captured through questions concerning gender, age, and academic level, and their thoughts and behaviours regarding internet gaming, social media, smartphone and internet use habits.

Smartphone Addiction Scale Short-Version: The 10-item concise self-report scale is based on the Smartphone addiction scale (SAS, Kwon *et al.* 2013a). The Smartphone Addiction Scale-Short Version (SAS-SV) was used to assess smartphone addiction (Kwon *et al.*, 2013b). The SAS-SV was used to measure smartphone addiction among South Korean adolescents. Each item is measured on a 6-point Likert-type scale with 1 denoted by "Strongly disagree" and 6 denoted by "Strongly agree". The 10 items generate a score between 10 and 60, which is employed to categorise the smartphone use practices of the preservice teachers as either normal or potentially addictive. It has also been found to be an effective measure of smartphone addiction among young adults in the United States (Harris *et al.*, 2020). The SAS-SV scale proposes a cut-off point of 31 for males, which is two points lower than the cut-off point of 33 for females in order to identify the potential diagnostic pathology of usage (Kwon *et al.*, 2013b). This current study yielded Cronbach's alpha coefficients of $\alpha = .91$ and McDonald's alpha coefficients of $\omega = .92$.

The Social Media Addiction Scale: The 6-item Bergen Social Media Addiction Scale (BSMAS) was administered to assess one's social media addiction level. Participants were asked to report their experiences using social media within 12 months. Each item in the scale reflected one of the core addiction components (salience, modification, mood, tolerance, relapse, and withdrawal conflict) proposed by Griffiths *et al.* (2017). A 5-point Likert-type scale was considered for the rating (1 being "very rarely" to 5 being "very often"). A higher aggregated score derived from the BSMAS exhibited a higher chance of severe addiction to social media. The BSMAS score of 19 or higher in a score range of 5 to 30 was suggested to be indicative of PSMU risk (Bányai *et al.* 2017). This current study yielded Cronbach's alpha coefficients of $\alpha = .91$ and McDonald's alpha coefficients of $\omega = .92$.

The Gaming Addiction Disorder Scale 9 Short Form: The 9-item Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) (Pontes & Griffiths, 2015) is a brief self-report screening estimate based on the nine Diagnostic and Statistical Manual of Mental Disorders (DSM-5) standards for Internet Gaming Disorder (American Psychiatric Association, 2013). It has been widely used to estimate subtypes and the prevalence of Internet Gaming Disorder (IGD) in a general population. The IGDS9-SF estimates the subtypes and prevalence of IGD by scrutinising online or offline gaming activities over 12 months. The scale yields an absolute score ranging between 9 and 45. A cut-off point of 32 was designated (Qin *et al.*, 2020). Scores above this cut-off are indicative of problematic gaming. This current study yielded Cronbach's alpha coefficients of $\alpha = .86$ and McDonald's alpha coefficients of $\omega = .87$.

The Problematic Internet Use Scale Short Form 9: The 9-item Problematic Internet Use Questionnaire Short Form (PIUS-SF-9), developed by Koronczai *et al.* (2011), was employed to determine individuals at risk of developing problematic Internet use and those who were not. The scale differentiates between those at risk of PIU and those not at risk, utilising a statistically established cut-off point of 22, above which internet use is deemed problematic. The minimum and maximum scores vary between 9 and 45 points, respectively (Koronczai *et al.*, 2011). This current study yielded Cronbach's alpha coefficients of $\alpha = .89$ and McDonald's alpha coefficients of $\omega = .90$.

Technology Fatigue Scale: The Revised Piper Fatigue Scale (PFS), a self-report measure, was employed to measure technology-related fatigue (TRF) to better align with the specific symptoms and experiences associated with prolonged use of digital devices. The PFS has 22 items and was developed by Piper *et al.* (1998). The scale measures subjective perceptions of fatigue in an individual. It has 4 dimensions which include: Dimension 1 - Behaviour/intensity for measuring the impact of fatigue and its intensity on daily life activities; Dimension 2 - Affective for measuring the emotional meaning of fatigue; Dimension 3 - Sensory, which reflects the physical, mental, and emotional symptoms of fatigue; and Dimension 4 - Cognitive/mental for measuring fatigue impact on mental status and cognitive functions. The number of dimensions and items in the scale remained the same, but the wording of the items was modified to reflect TRF. For example, "I feel fatigued after prolonged use of digital devices" and "I have difficulty focusing on tasks while using digital devices''. The sum for each dimension is derived by totalling the responses in that dimension and dividing them by items in the specific dimension. The total fatigue score is derived by totalling the response preferences of all items and dividing them by the total items in the scale. Higher TRF scores predict intense perceived fatigue statuses (Can, 2001). Cronbach's alpha for the global scale is $\alpha = 0.97$ (Piper *et al.*, 1998). In the current study, the Cronbach alpha value and McDonald's omega value of the scale were found to be $\alpha = 0.91$ and $\omega = .92$, respectively.

Social Desirability Scale: The Strahan and Gerbasi (1972) short version of the Marlowe–Crowne social desirability scale (Crowne & Marlowe, 1960) was utilised to control likely response bias better. This short version has illustrated adequate psychometric robustness and comprises 10 true/false (1 = True, 2 = False) items of the original 33 item scale, and it has been used in studies on addiction (Herrero *et al.*, 2019; Broadus & Evans 2015). We reversed negative indicators to illustrate the reflection of higher levels of social desirability. In this study, the mean and standard deviation of the 10-item scores were m = 2.61 to 3.32, and SD = 0.32 to 1.12, respectively. Social desirability scores were associated with subtypes of digital addiction scores ($r = -.43$ to $-.47$, $p < .05$), suggesting that preservice teachers moderately reported their digital addiction symptoms.

Statistical tests

The data on Preservice teachers' Smartphone Addiction, Social Media Addiction, Gaming Addiction Disorder, and Problematic Internet Use were estimated utilising frequency (f) distribution, arithmetic mean values (X), independent-samples T-test, bivariate correlation (Pearson *r*), and regression analyses (stepwise). Analyses were conducted to determine the relationships between variables and technology-related Fatigue. Before data analysis, the assumptions for the regression analysis were examined. The skewness and kurtosis values were calculated for the normality assumption, and they fell within a normal distribution's acceptable range. The presence of outliers was also estimated, but none were identified. Pearson product-moment correlation coefficients (r), tolerance values, and variance inflation factors (VIF) were calculated to test the assumption of multicollinearity. VIF must be at most four, and tolerance must stay below 0.20. (Tabachnick & Fidell, 2007). VIF values ranged from 1.077 to 1.439, and tolerance values ranged from 0.695 to 0.929, according to the findings. Consequently, the assumption of multicollinearity has been confirmed. In addition, the linearity and homoscedasticity assumptions were estimated by generating a scatter plot of the standardised residuals. The distribution of residuals was relatively rectangular, with the majority of scores gathering in the centre. In the current study, the assumptions of linearity and homoscedasticity were satisfied. Microsoft Excel 365 was used to input the data. The data were encoded and processed using Jamovi 2.3.18 (The Jamovi Project, 2022; RCore Team, 2021; Fox & Wesberg, 2020).

RESULTS

Descriptive traits

The sociodemographic traits of the preservice teachers are illustrated in Table 1.The majority (189, 85.9%) of the preservice teachers owned personal digital devices. According to the survey results, about 50.5% (111) of the preservice teachers utilise the internet for educational purposes; 31.4% (69) communicated online with friends; 15% (33) shared online resources; and 3.1% (7) used it for other purposes. All the preservice teachers were members of a social networking platform. Besides, all of them were interested in playing games on their smartphones or other display devices such as laptops, desktops, or tablets. Finally, about two-thirds of the respondents (148, 67.3%) admitted that internet use affects their resting time.

Table 1: Sociodemographic Traits (N = 220)

Variables		M	SD	f (%)
The students owned a personal digital device (e.g. smartphone, personal computer)	Yes			189 (85.9)
	No			31 (24.1)
Hours spent on smartphone		9.11	1.12	
Member of a social networking platform	Yes			220 (100)
	No			-
Number of friends connections on social network platform	1000 friends' connections or less			110 (50)
	Above 1000 friends' connections			110 (50)
Hours spent on social media		8.9	1.59	
Creating new friends on social network platform	Yes			141 (64.1)
	No			79 (35.9)
Are you interested in gaming?	Yes			220 (100)
	No			-
Mode for playing games	Online			73 (33.2)
	Offline			147 (66.8)

Hours spent gaming		8.1	0.91	
Experience with Internet	0 - 10 years			169 (76.8)
	Above 10 years			51 (23.2)
Daily Internet usage time	Less than 1 hour			27 (12.3)
	1 - 3 hours			79 (35.9)
	More than 3 hours			114(51.8)
Active internet service	Yes			181 (82.3)
	No			39 (17.7)
Purposes of Internet use	Educational purpose			111 (50.5)
	Communicate with friends			69 (31.4)
	Share resources			33 (15.0)
	other			7 (3.1)
Hours spent on the internet		8.73	2.31	
Ownership of Data package	Yes			155 (70.5)
	No			65 (29.5)
Does internet use affect rest time	Yes			148 (67.3)
	No			72 (32.7)

M = mean; SD = Standard Deviation; f = Frequency; L = level; Other = entertainment, gaming etc.

The mean score Smartphone Addiction Scale (36.65 ±13.46), Social Media Addiction (18.07 ±7.19), Internet Gaming Disorder Scale (19.44 ±7.98), and Problematic Internet Use Scale (25.65 ±9.66) were found to be above average scores. Regarding the Piper Fatigue Scale, we found an average score, with students mostly experiencing sensory fatigue (2.76 ±1.16). Table 2 illustrates the details of the results.

Table 2. The Distribution of the SAS-SV, BSMAS, IGDS9-SF, PIU-SF-9, and PFS mean scores of the preservice teachers.

Psychometric scale	Scale dimensions	Range of obtainable values (min-max)	Range of obtained values (min-max)	M	SD
SAS-SV		10 - 60	13 - 60	36.65	±13.46
BSMAS		6 - 30	7 - 30	18.07	±7.19
IGDS9-SF		9 - 45	9 - 45	19.44	±7.98
PIU-SF-9		9 - 45	9 - 43	25.65	±9.66
PFS					
	Behaviour/ Intensity	1 - 6	1.0 - 4.8	2.31	±1.09
	Affective	1 - 5	1.0 - 5.0	2.68	±1.16
	Sensory	1 - 5	1.0 - 4.8	2.76	±1.16
	Cognitive/ Mental	1 - 6	1.0 - 5.0	2.63	±1.21

M = mean; SD = Standard Deviation

Comparing differences between addiction levels of DA subtypes and TRF

OnTable 3, preservice teachers who were identified as "At Risk" for SAS-SV, BSMAS, IGDS9-SF, and PIU-SF-9, reported higher mean values for technology-related fatigue. Compared to those labelled as not at risk, preservice teachers who were categorised as at risk of smartphone addicts were found to have higher levels of fatigue (*p < .001*). Likewise, preservice teachers who were categorised as at risk of social media addiction were found to have higher levels of fatigue (*p < .001*). Moreover, preservice teachers categorised as at risk of internet gaming disorder addicts and problematic internet users reported significantly higher fatigue levels (*p < .001*), respectively.

Table 3: Relationships between the BEIS-10, PFS, and SAA mean scores according to their SAS-SV, BSMAS, IGDS9-SF, and PIU-SF-9 levels.

	Not at Risk		At Risk							
	N	M (±SD)	N	M (±SD)	Statistic	df	p	Mean difference	SE difference	Effect Size
SAS-SV										
PFS	77	8.28 (2.06)	143	11.5 (2.91)	9.59	202	< .001	3.24	0.338	1.29
BSMAS										
PFS	108	9.03 (2.57)	112	11.7 (2.92)	7.15	216	< .001	2.65	0.371	0.963
IGDS9-SF										
PFS	202	10.2 (2.92)	18	12.7 (3.58)	2.94	19.1	0.008	2.56	0.869	0.782
PIUS-9-SF										
PFS	75	9.02 (3.16)	145	11.1 (2.76)	4.82	133	< .001	2.07	0.430	0.700

Note: SAS-SV: Smartphone Addiction Scale - Short Version; BSMAS: Bergen Social Media Addiction Scale; IGDS-9-SF Internet Gaming Addiction Scale - 9- Short Form; PIUS-SF-9: Problematic Internet Use Scale-Short Form-9; PFS: Piper Fatigue Scale

Correlation analysis

Correlational statistics for SAS-SV, BSMAS, IGDS9-SF, PIU-SF-9, and PFS are in Table 4. The data illustrate that the fatigue measure significantly correlated positively with social media addiction (*r = 0.354, p < .001*), internet gaming disorder (*r = 0.444, p < .001*), and problematic internet use (*r = 0.176, p < .001*). Regarding the dimension of the PFS, SAS-SV scores had a significant positive link with the 4 dimensions of fatigue scores: Behaviour/intensity (*r = 0.212, p < .001*), Affective (*r = 0.181, p < .001*), Sensory (*r = 0.239, p < .001*), and Cognitive/mental (*r = 0.281, p < .001*). Besides, BSMAS scores indicated a significant positive link with the 4 dimensions of fatigue scores: Behaviour/intensity (*r = 0.288, p < .001*), Affective (*r = 222, p < .001*), Sensory (*r = 0.149, p < .05*), and Cognitive/mental (*r = 0.278, p < .001*). Moreover, IGDS9-SF scores demonstrated a significant positive link with Behaviour/intensity (*r = 0.386, p < .001*), Affective (*r = 0.408, p < .001*), and Cognitive/mental (*r = 0.278, p < .001*), while PIUS-SF-9 illustrated a significant low positive nexus with Behaviour/intensity (*r = 0.160, p < .05*) and Sensory (*r = 0.152, p < .05*).

Table 4: The correlation between the SAS-SV, BSMAS, IGDS9-SF, PIUS-SF-9, BEIS-10, PFS, and SAA.

	SAS_SV		BSMAS		IGDS9_SF		PIUS_SF_9	
Behaviour/intensity	0.212	**	0.288	***	0.386	***	0.160	*
Affective	0.181	**	0.222	***	0.408	***	0.074	
Sensory	0.239	***	0.149	*	0.069		0.152	*
Cognitive/mental	0.281	***	0.278	***	0.316	***	0.084	

Note. * p < .05, ** p < .01, *** p < .001

SAS-SV: Smartphone Addiction Scale - Short Version; BSMAS: Bergen Social Media Addiction Scale; IGDS-9-SF Internet Gaming Addiction Scale - 9- Short Form; PIUS-SF-9: Problematic Internet Use Scale-Short Form-9; PFS: Piper Fatigue Scale

Regression analysis

The model has an endogenous variable, technology-related fatigue, and four exogenous variables, SA, PSMU, IGD, and PIU. To calculate the best relationship and extent of the exogenous and endogenous variables, we performed a stepwise linear regression analysis to observe which variables play a critical role in predicting the endogenous variable.

The results of the stepwise regression estimate regarding the fatigue scores (endogenous variable) with the predictors of smartphone addiction, social media addiction, internet gaming disorder, and problematic internet use are illustrated in Table 5. The predictors explained a total variance of 27.9% ($R^2 = 0.279$) in fatigue levels and appeared to be significant predictors of fatigue ($F = 20.8, p < .001$). Besides, smartphone addiction explained 12% ($R^2 = 0.120$) of the variance in response to fatigue levels ($F = 29.8, p < .001$). Nonetheless, the IGD variable is not statistically significant at the 5% significance level. Likewise, standardised beta coefficients are all greater than 0, demonstrating a negative association, which signifies that the higher the digital addiction, the higher the fatigue level. Thus, technology-related fatigue is affected by the DA subtypes.

Table 5: Stepwise regression analysis predicting PFS

	Model	β	t	p	R	R^2	F	p
1	SAS-SV	0.347	13.32	< .001	0.347	0.120	29.8	< .001
2	SAS-SV	0.268	4.21	< .001	0.437	0.191	25.6	< .001
	BSMAS	0.278	4.36	< .001				
3	SAS-SV	0.256	4.24	< .001	0.527	0.278	27.7	< .001
	BSMAS	0.099	1.42	0.156				
	IGDS9-SF	0.346	5.09	< .001				
4	SAS-SV	0.261	4.287	< .001	0.528	0.279	20.8	< .001
	BSMAS	0.115	1.566	0.119				
	IGDS9-SF	0.352	5.127	< .001				
	PIUS-SF-9	-0.045	-0.689	0.492				

SAS-SV: Smartphone Addiction Scale - Short Version; BSMAS: Bergen Social Media Addiction Scale; IGDS-9-SF Internet Gaming Addiction Scale - 9- Short Form; PIUS-SF-9: Problematic Internet Use Scale-Short Form-9.

In order to analyse the link between DA subtypes and the dimensions of fatigue, a stepwise regression estimate was performed. The outcomes are shown in Table 6.

Estimations revealed statistically significant partial regression coefficients and models (p <.001). Smartphone addiction had a significant relationship with all dimensions of fatigue, explaining 4.5% of the variance in behaviour/intensity, 3.3% of affective, 5.7% of sensory, and 7.9% of cognitive/mental. Problematic social media use was not significantly related to the sensory dimension. However, problematic social media use is significantly related to behaviour/intensity, affective, and cognitive/mental dimensions. Smartphone addiction and problematic social media use together explained 10.2% of the variance in the behaviour/intensity dimension, 6.4% in the affective dimension, and 12.2% in the cognitive/mental dimension. Besides, internet gaming disorder did not have a significant relationship with the sensory dimension, but it had a significant relationship with the behaviour/intensity, affective, and cognitive/mental dimensions. Smartphone addiction, problematic social media use, and internet gaming disorder explained 17.5% of the variance in responses to the behaviour/intensity, 17.9% in the affective, and 15.9% in the cognitive/mental dimensions of technology-related fatigue.

Table 6: Stepwise regression analysis predicting dimensions of PFS

		Behaviour/intensity		**Affective**		**Sensory**		**Cognitive/mental**	
	Model β	**R²**	β	**R²**	β	**R²**	β	**R²**	
1	SAS-SV	0.212	0.045	0.181	0.033	0.239	0.057	0.281	0.079
2	SAS-SV	0.142	0.102	0.128	0.064	-	-	0.220	0.122
	BSMAS	0.248		0.185		-		0.215	
3	SAS-SV	0.131	0.175	0.115	0.179	-	-	0.213	0.159
	BSMAS	0.084		-0.020		-		0.100	
	IGDS9-SF	0.319		0.400		-		0.225	
4	SAS-SV	-	-	-		-	-	-	-
	BSMAS	-		-		-		-	
	IGDS9-SF	-		-		-		-	
	PIUS-SF-9	-		-		-		-	

SAS-SV: Smartphone Addiction Scale - Short Version; BSMAS: Bergen Social Media Addiction Scale; IGDS-9-SF Internet Gaming Addiction Scale - 9- Short Form; PIUS-SF-9: Problematic Internet Use Scale-Short Form-9

DISCUSSION AND CONCLUSIONS

Literature on digitally-connected devices and apps has traditionally cautioned about their likely deleterious outcomes on users' health (WHO, 2015). This study aimed to determine whether the subtypes of DA explain technology-related fatigue. The findings illustrate that the DA subtypes are positively linked with the dimensions of TRF though not all the correlations were significant. The findings of this study support earlier cross-sectional studies' findings that fatigue and

DA subtypes are positively correlated (Liang *et al.*, 2022; Lekkas *et al.*, 2022; Whelan *et al.*, 2020; Priya & Subramaniyam, 2020; Borhany *et al.*, 2018; Dhir *et al.*, 2018; Yang *et al.*, 2017; Oberst *et al.*, 2017; Elhai *et al.*, 2016; Brand *et al.*, 2016; Hellström *et al.*, 2015; Ho *et al.*, 2014; Lin *et al.*, 2013; Ayanniyi *et al.*, 2010). Our study is pioneering in Ghana to measure DA subtypes and their negative influence on TRF in the Ghanaian cultural context.

In this study, DA subtypes (SA, SMA, IGD, and PIU) were identified to be linked with positive effects on TRF, although there was extant literature to support some of these findings. Literature has shown a reciprocal association between SA and TRF. The current study generated a positive link between SA and TRF, and SA was the most important factor influencing TRF. This study is in line with Sert *et al.* (2019) and Dora *et al.* (2021), who found a positive relationship between SA and TRF. Besides, a study conducted in Saudi Arabia (Khan, 2008) demonstrated that the risk of SA was significantly higher among students experiencing higher fatigue levels. Preservice teachers may use smartphones to cope with depression, stress, anxiety, loneliness, strained relationships, low academic achievement (Hawi & Samaha, 2016), and boredom (Whelan *et al.*, 2020). Moreover, smartphone overuse by preservice teachers can affect their abilities to perform physical and cognitive activities (Mizuno *et al.*, 2011; Hagberg, 1981) as a result of mental and physical fatigue (Lekkas *et al.*, 2022) and may adversely influence their decision-making abilities (Gantois *et al.*, 2020). Furthermore, SA among preservice teachers may result in heightened visual impairments, problems with interpersonal aptitudes, and musculoskeletal symptoms such as worsened fatigue in the shoulders and neck due to forward head posturing (Priya & Subramaniyam, 2020; Lee *et al.*, 2017; Kim & Koo, 2016). Problematic internet use plays a crucial role in fatigue (Lin *et al.*, 2013).

In our study, SMA positively correlated with severe fatigue symptoms among the preservice teachers. This finding is similar to findings in multiple studies (Oberst *et al.*, 2017; Elhai *et al.*, 2016; Brand *et al.*, 2016; Ho *et al.*, 2014; Lin *et al.*, 2013). Other literature in line with our findings reported that obsessive use of social media positively predicted the disposition to experience fatigue (Hattingh *et al.*, 2022; Tandon *et al.*, 2021a; Tandon *et al.*, 2021b; Dhir *et al.*, 2018) and also causes adverse emotions such as a dearth of energy, fatigue, and stress (Ballerini *et al.*, 2022; Ravindran *et al.*, 2014; Maier *et al.*, 2012). Our findings illustrated the high prevalence of SMA in preservice teachers resulting from the long duration and inappropriate control over social media use. When disproportionate social media users cannot control their use behaviours appropriately, it develops obsessive use behaviour (Parylak *et al.*, 2011; Meerkerk *et al.*, 2010; Hirschman, 1992). In line with our study, other studies (Dhir *et al.*, 2018; Boksem & Tops, 2008; van der Linden & Eling, 2006; Boksem *et al.*, 2005) underlined that obsessive use of social media involves different psychological and physiological conditioning that may mandate intensive cognitive processing and exhaust mental strength and, consequently, lead to fatigue among preservice teachers. In this study, PIU had a significant positive correlation with TRF and supported the findings by Sert *et al.* (2019) and Kim *et al.* (2010), although PIU was not a significant predictor of TRF. This finding may imply that preservice teachers may relish the social benefits of internet use because social media is growing in significance (Wang *et al.*, 2016). However, Dol (2016) discovered a relationship between daily internet use and fatigue symptoms of university students, which is similar to our findings. The results of our study also agree with those of Bachleda and Darhiri (2018), who reported that students with PIU exhibit significantly higher levels of physical and mental fatigue than those without PIU. Additionally, Borhany *et al.* (2018) and Hellström *et al.* (2015) discovered a significant relationship between musculoskeletal problems (headache, neck, and wrist) and prolonged internet use. Furthermore, the findings in this study agree with the works of multiple scholars (Liang *et al.*, 2022; Bener *et al.*, 2019; Bener *et al.*, 2016), who reported a positive relationship between PIU and fatigue symptoms.

IGD correlated positively with severe fatigue symptoms in our study and was also a significant predictor of TRF. This finding is consistent with previous literature (Ohayon & Roberts, 2021; Männikkö *et al.*, 2015; Mentzoni *et al.*, 2011; Choi *et al.*, 2009), which reported a positive link between IGD and TRF. This finding implies that preservice teachers who experience severe gaming disorder may develop psychophysical health (Liu & Peng, 2009) or musculoskeletal symptoms (Männikkö *et al.*, 2015; Hellström *et al.*, 2015; Lui *et al.*, 2011), which can have a negative impact on their well-being (Goh *et al.*, 2019) and learning success (McLean & Griffiths, 2013). However, some studies contradict our findings on the psychological and physical health conditions associated with IGD. Johnson *et al.* (2013) discovered heightened well-being among gamers, while Lobel *et al.* (2017) discovered no link between psychosocial well-being and playing digital games. In addition, a study discovered no significant correlation between players of psychological functioning and distinct digital game (Von Der Heiden *et al.*, 2019). Laato *et al.* (2022) studied the effect of digital games on psychological well-being and found that playing digital games is linked with improved psychological well-being, and it suggests that digital games can be used as a mechanism for reducing fatigue and fostering well-being. Rauti *et al.* (2020) discovered six social affordances in digital games and demonstrated that the game teaches various social dexterities varying from group interaction to bartering and negotiation. In this study, the number of preservice teachers at risk of IGD was lower. The reason could be the use of the word “Internet” in IGD. Studies that particularly concern IGD tend to indicate a lower prevalence than those that study gaming disorder (Fam, 2018; Starcevic, 2013). Thus, the possibility exists that those who were not at risk of IGD may be using digital games to enhance their well-being and decrease fatigue and boredom associated with academic life. In addition, preservice teachers’ gaming behaviours and social interactions may have a greater impact on their well-being than the actual games they play.

In conclusion, this study’s findings support a relationship between the subtypes of digital addiction (SA, SMA, IGD, and PIU) and TRF among the sampled preservice teachers in Ghana. The study’s results indicate that SA, SMA, IGD, and PIU positively correlate with the dimensions of TRF, and the multiple regression illustrates that SA and IGD are significant predictors of technology-related fatigue. These findings underline the importance of discoursing DA among preservice teachers in Ghana and developing strategies to mitigate its adverse effects on their well-being. The study also contributes to the current body of literature by focusing on the context of preservice teachers in Ghana and the impact of different forms of DA on TRF. Future research could explore potential interventions to reduce the negative effects of digital addiction on technology-related fatigue among public and private college of education students in Ghana and other contexts.

Implications for the study

The study’s findings have several implications for digital addiction and technology-related fatigue. Firstly, the study highlights the importance of considering different forms of digital addiction when studying the impact of technology use on well-being. The subtypes of digital addiction (SA, SMA, IGD, and PIU) were found to be positively linked with technology-related fatigue, suggesting that it is important to consider the specific ways individuals use digital devices when studying the effects of technology use on well-being. Secondly, the study highlights the importance of considering the cultural context in which technology use occurs. The study was conducted among university preservice teachers in Ghana. Notwithstanding, the findings suggest that the relationship between DA and technology-related fatigue may differ in different cultural contexts. This finding emphasises the need for further studies in diverse cultural contexts to better comprehend the effects of technology use on well-being. Thirdly, the study has implications for educators and policymakers. The findings suggest that DA among university students, including preservice teachers, can negatively affect well-being, including technology-related fatigue. This highlights the need for strategies to mitigate the negative effects of digital addiction on student well-being, such as developing policies and guidelines for the responsible use of digital devices in the educational setting. Lastly, the study has implications for individuals who use digital devices. The findings suggest that excessive use of digital devices can negatively affect well-being, including technology-related fatigue. This highlights the importance of being aware of one's use of digital devices and taking steps to limit excessive use, such as setting limits on device use and taking regular breaks. Overall, this study highlights the need for further research on the relationship between digital addiction and technology-related fatigue in different cultural contexts and the importance of considering different forms of digital addiction when studying the impact of technology use on well-being. It also has important implications for educators, policymakers, and individuals who use digital devices.

Limitations and future works

The study is constrained by its cross-sectional method, which prevents the establishment of a causal relationship between DA subtypes and fatigue driven by technology use. Longitudinal studies are needed to examine the direction and causality of the relationship. The sample in the study was limited to university preservice teachers in Ghana. Therefore, the results need to be more generalizable to other populations, such as preservice teachers in colleges of education or other countries. Besides, studies should be conducted in distinct cultural contexts to examine the generalizability of the findings across cultures. The study relied on self-report measures, which are subject to bias and may not accurately reflect the participants' true experiences, although the study controlled for social desirability. Finally, the study did not consider other factors contributing to technology-related fatigue, such as sleep quality, physical activity, or other mental health issues. In addition, future studies should also examine the impact of digital addiction and technology-related fatigue on academic performance among university preservice teachers.

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