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CatBoost Classification of Digital Burnout Based on Technostress, Online Boundary Control, and Sleep Procrastination

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ABSTRACT

Objective: This study aimed to classify digital burnout severity among adult digital technology users in Canada using the CatBoost machine learning algorithm based on technostress, online boundary control, and sleep procrastination.

Methods and Materials: This applied, quantitative, cross-sectional, and predictive classification study was conducted among 486 adult digital technology users residing in Canada. Participants were selected through convenience sampling and completed standardized self-report measures assessing digital burnout, technostress, online boundary control, and sleep procrastination. Digital burnout was categorized into low, moderate, and high classes and used as the target outcome variable. Technostress, online boundary control, and sleep procrastination were entered as predictor variables. The dataset was divided into training and testing subsets, and the CatBoost classifier was developed using cross-validation and hyperparameter tuning. Model performance was evaluated using accuracy, precision, recall, F1-score, ROC-AUC, Cohen's kappa, confusion matrix, and feature importance indices.

Findings: The CatBoost model demonstrated strong classification performance in predicting digital burnout severity. The overall accuracy of the model was 0.84, with a weighted F1-score of 0.84 and a macro-average ROC-AUC of 0.91. Cohen's kappa coefficient was 0.75, indicating substantial agreement between observed and predicted burnout classes. Class-specific results showed that the model classified low digital burnout with precision = 0.88, recall = 0.91, and F1-score = 0.89; moderate digital burnout with precision = 0.79, recall = 0.79, and F1-score = 0.79; and high digital burnout with precision = 0.84, recall = 0.81, and F1-score = 0.82. Feature importance analysis showed that technostress was the strongest predictor, followed by sleep procrastination and online boundary control.

Conclusion: The findings indicate that CatBoost can accurately classify digital burnout severity based on psychological and behavioral predictors. Technostress, sleep procrastination, and online boundary control appear to be meaningful indicators for identifying individuals at risk of higher digital burnout.

Keywords: *Digital burnout; CatBoost; technostress; online boundary control; sleep procrastination; machine learning; classification.*

1. Introduction

The rapid expansion of digital technologies has transformed the organization of work, education, social relationships, health information behavior, and everyday self-regulation. Digital platforms, smartphones, learning management systems, online communication applications, and remote work infrastructures have increased access, flexibility, and productivity, but they have also produced new psychological pressures associated with continuous connectivity and constant responsiveness. In contemporary digital environments, individuals are increasingly expected to remain available, process large volumes of information, manage multiple communication channels, and regulate their attention across overlapping work, academic, and personal domains. These conditions have intensified interest in digital burnout as a psychological response to prolonged and poorly regulated digital engagement. Digital burnout refers to a state of emotional exhaustion, cognitive fatigue, reduced motivation, and psychological depletion arising from excessive or invasive use of digital technologies. Unlike general burnout, which has traditionally been conceptualized in occupational settings, digital burnout is closely linked to technology-mediated overload, online boundary disruption, and insufficient psychological recovery from screen-based demands. The validation of the Digital Burnout Scale in recent research has further supported the need to examine digital burnout as a distinct and measurable construct in public health and behavioral science research (Choi & Kim, 2024).

The emergence of digital burnout should be understood within the broader transformation of the digital workplace and online life. Digital work arrangements, virtual collaboration, hybrid education, and platform-mediated communication have changed how individuals allocate cognitive resources and maintain boundaries between work, study, rest, and private life. The digital workplace can provide autonomy and flexibility when designed appropriately, but it may also intensify workload, increase interruptions, and blur temporal and spatial boundaries between personal and professional roles (Wang & Parker, 2023). From a work design perspective, sustainable virtual work requires attention to demands, resources, autonomy, support, and manageable technology-mediated communication patterns. When these elements are not adequately regulated, digital tools may become sources of strain rather than support. In this context, digital burnout is not merely the result of using technology frequently; rather, it reflects the interaction between digital demands, limited recovery opportunities, weak boundary control, and maladaptive behavioral routines that prolong engagement with digital devices beyond functional necessity.

One of the central constructs related to digital burnout is technostress. Technostress refers to stress experienced as a result of the use, complexity, overload, uncertainty, invasion, or insecurity associated with information and communication technologies. In digitalized academic and occupational settings, technostress can develop when users feel pressured to work faster, respond immediately, adapt continuously to changing systems, or remain reachable outside formal working hours. Research on teachers and researchers during the COVID-19 pandemic showed that technostress was meaningfully related to burnout experiences, highlighting the psychological costs of prolonged technology-mediated work under conditions of uncertainty and high demand (Marrinhas et al., 2023). Similarly, occupational health psychology has increasingly recognized that contemporary work stressors are shaped by cross-cultural and technological changes, making it necessary to examine digital stressors as part of twenty-first-century mental health and occupational well-being challenges (Sarfraz et al., 2022). The growing literature on techno-social stress also suggests that social network sites and digitally mediated social interaction can function as stress-inducing environments when they amplify comparison, constant monitoring, information overload, and interpersonal pressure (Naga & Ebardo, 2025).

Technostress is particularly relevant to digital burnout because it represents the stress-generating quality of technology use rather than the mere quantity of screen time. Individuals who use digital tools for many hours may not necessarily experience burnout if their technology use is autonomous, predictable, and bounded. However, when digital engagement is accompanied by perceived overload, interruptions, expectations of constant availability, and difficulty disengaging, the risk of emotional exhaustion increases. Practical discussions of technostress in online work environments emphasize the importance of work–life balance strategies, digital availability management, and intentional regulation of communication demands (Clark, 2025). In this sense, technostress provides a theoretically strong predictor of digital burnout because it captures the subjective burden imposed by digital systems. It also connects digital burnout to broader questions of boundary management, as technology-related pressure often operates by extending work, study, or social demands into times that would otherwise be used for rest, recovery, or personal activities.

Online boundary control is therefore another critical factor in explaining digital burnout. Boundary control refers to the perceived ability to regulate the timing, frequency, and intrusiveness of digital demands and to maintain separation between online obligations and personal life. In digital environments, boundary control is challenged by smartphones, notifications, instant messaging platforms, social media, email, and institutional or workplace systems that create expectations of rapid response. Research on social media and well-being across work, home, and transitional spaces suggests that digital platforms can influence psychological well-being not only during formal work or study time but also in "in-between" moments where individuals are psychologically shifting between roles (Klingelhoefer & Meier, 2023). When people lack control over online availability, digital demands can fragment attention and reduce recovery even outside official work or academic hours. Off-time work-related smartphone use has also been linked to bedtime procrastination among public employees, indicating that after-hours digital work can interfere with sleep-related self-regulation and extend the psychological presence of work into the night (Hu et al., 2022).

Boundary control is especially important because digital burnout often develops through cumulative micro-demands rather than through a single overwhelming event. Repeated notifications, expectations of responsiveness, unfinished digital tasks, and social or occupational pressure to remain connected may gradually erode recovery capacity. In online education, students' focus, time management, and personal energy have been shown to be important components of adaptation to digital learning conditions (Grah & Penger, 2022). These findings suggest that the psychological consequences of digital engagement depend partly on whether individuals can organize attention and energy in ways that prevent digital activities from dominating the entire day. When online boundary control is weak, technology use may become intrusive and difficult to terminate, contributing to a state of sustained cognitive and emotional activation. Over time, this activation may reduce the individual's ability to recover from digital demands and increase vulnerability to burnout symptoms.

Sleep procrastination is a third key construct in the study of digital burnout. Sleep procrastination generally refers to the voluntary delay of going to bed despite the absence of external circumstances preventing sleep. It is often interpreted as a failure of self-regulation, particularly when individuals continue engaging in low-priority activities such as scrolling, watching videos, messaging, gaming, or browsing even after intending to sleep. Bedtime procrastination became especially salient during periods of intensified digital life, including pandemic-related lockdowns, when routines were disrupted and technology use increased (Oliveira et al., 2022). Recent work has connected bedtime procrastination to sleep quality, psychological well-being, stress, and problematic digital behavior, suggesting that delayed sleep is both a behavioral outcome of digital overuse and a mechanism through which digital overuse may impair mental health. Studies of hostellers and day scholars, for example, have examined bedtime procrastination alongside thought control, indicating that cognitive self-regulation and pre-sleep mental activity are relevant to the tendency to delay sleep (Roy et al., 2022).

A growing body of evidence links problematic smartphone use, sleep problems, and bedtime procrastination. Research has shown that bedtime procrastination can mediate or explain the relationship between problematic smartphone use and poor sleep quality, indicating that digital device use may impair sleep partly by encouraging delayed bedtime routines (Correa-Iriarte et al., 2023). Similar findings among adolescents have demonstrated associations among bedtime procrastination, sleep quality, and problematic smartphone use, with mediation pathways suggesting that smartphone-related behaviors can indirectly undermine sleep through procrastination processes (Bozkurt et al., 2024). Smartphone addiction has also been associated with bedtime procrastination and other behavioral outcomes among adolescents, reinforcing the role of mobile technologies in disrupting self-regulated evening routines (Caninsti & Rahayu, 2024). Moreover, research on problematic smartphone use and sleep problems has identified sleep-related compensatory health beliefs and bedtime procrastination as important psychological mechanisms, suggesting that individuals may justify delayed sleep by underestimating its consequences or believing that sleep loss can be compensated later (An & Zhang, 2024).

The importance of sleep procrastination for digital burnout lies in its direct connection to recovery. Sleep is a central mechanism of psychological restoration, emotional regulation, cognitive functioning, and stress recovery. When individuals repeatedly postpone sleep due to digital

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engagement or poor self-regulation, they may experience insufficient recovery from daily technological demands. This may intensify fatigue, irritability, cognitive overload, and emotional exhaustion. Daily diary evidence has indicated that stressful days may be followed by sleep postponement, and such postponement can be associated with poorer sleep outcomes (Schmidt et al., 2023). Insomnia severity has also been linked with bedtime procrastination, with emotion regulation strategies moderating this relationship, suggesting that the tendency to delay bedtime may be particularly problematic among individuals with weaker emotional regulation capacities (Jeon et al., 2023). Broader discussions of sleep disturbance and psychological well-being further emphasize that poor sleep is not only a health outcome but also a risk condition for reduced mental wellness and functional impairment (Bahmani et al., 2024; Kamene, 2025).

The relationship between digital technologies and sleep-related self-regulation has also been examined in adolescent and university populations. An umbrella review of digital device use and sleep in adolescents has highlighted the broad relevance of screen exposure, device habits, and digital routines for sleep health (Fiore et al., 2025). Research during the COVID-19 outbreak found that mobile phone dependency was associated with sleep quality among college students, with bedtime procrastination and fear of missing out functioning as mediating factors (Huang et al., 2023). In nursing undergraduates, loneliness was associated with interpersonal sensitivity through the chain mediation of problematic internet use and bedtime procrastination, suggesting that digital and sleep-related behaviors may connect social-emotional vulnerability to psychological outcomes (Shi et al., 2024). Studies among university students during vocational internships have similarly emphasized sleep procrastination behavior and the need for psychological prevention strategies (Jiang et al., 2024). These findings collectively indicate that bedtime and sleep procrastination are not isolated sleep behaviors; rather, they are embedded in broader psychological, social, and digital self-regulation systems.

Procrastination research provides an important theoretical foundation for understanding sleep procrastination in the digital age. Temporal Motivation Theory emphasizes that delay behavior is shaped by expectancy, value, impulsiveness, and temporal distance, suggesting that even brief delays can accumulate into meaningful behavioral outcomes when immediate rewards outweigh delayed consequences (Bok et al., 2024). In digital contexts, the immediate reinforcement provided by smartphones, social media, online entertainment, or unfinished digital communication can easily override the delayed benefits of sleep. Procrastination has also been analyzed as a meaningful concept in nursing and professional contexts, where delay may affect performance, well-being, and responsibility management (Mai et al., 2025). Network analysis research has connected problematic smartphone use, exercise procrastination, and self-control, suggesting that procrastination-related behaviors are interrelated components of broader self-regulatory difficulty (He et al., 2025). Other studies have examined exercise procrastination and exercise addiction through socio-ecological frameworks, indicating that procrastination should be understood through individual, behavioral, and environmental correlates (Wang, 2026). In relation to bedtime, physical exercise has been associated with bedtime procrastination through the mediating roles of self-control and mobile phone addiction, further supporting the importance of behavioral regulation in sleep-related outcomes (Wang et al., 2025).

Digital burnout may also be connected to problematic smartphone use, phubbing, boredom, loneliness, and reduced self-control. During the COVID-19 outbreak, boredom proneness was associated with phubbing among college students through the mediating effects of self-control and bedtime procrastination, suggesting that digital disengagement difficulties may arise from both emotional and regulatory vulnerabilities (Meng & Xuan, 2023). Longitudinal evidence has connected mobile phone addiction, bedtime procrastination, and campus-based physical activity, indicating that digital habits and behavioral regulation can affect health-related routines over time (Deng & Li, 2025). These findings are relevant to digital burnout because they show that technology-related strain may emerge from a network of mutually reinforcing behaviors: excessive device use can delay sleep, delayed sleep can reduce self-control and emotional resilience, and reduced self-regulation can further intensify digital dependence. Even cultural and environmental factors influencing sleep, such as media exposure and music-related routines, have been discussed in relation to sleep quality among emerging adults, showing that sleep behavior is shaped by broader digital and lifestyle contexts (Sadjiarto & Susilo, 2024).

Although many studies have examined pairwise associations among technology use, technostress, sleep problems, and problematic smartphone behavior, fewer

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studies have applied machine learning methods to classify digital burnout severity based on psychological and behavioral predictors. Traditional statistical models are valuable for testing linear associations and mediation pathways, but digital burnout is likely to reflect nonlinear interactions among technostress, boundary control, and sleep procrastination. For example, high technostress may not lead to severe burnout among individuals with strong online boundary control and healthy sleep routines, whereas moderate technostress may become harmful when combined with low boundary control and high sleep procrastination. Machine learning classification models are useful in this context because they can detect complex patterns and interactions that may be difficult to capture through conventional regression models. CatBoost, as a gradient boosting algorithm based on decision trees, is particularly suitable for structured psychological data because it can model nonlinear relationships, handle interactions among predictors, and provide feature importance values that support interpretability.

The use of classification models may also have practical value for early identification and prevention. Digital burnout can impair functioning before individuals seek formal support, especially when symptoms are normalized as ordinary fatigue caused by modern digital life. Classification models can help distinguish low, moderate, and high burnout profiles and identify which predictors contribute most strongly to risk categorization. This is important because digital burnout may overlap with related forms of exhaustion, psychological distress, and occupational impairment. Burnout has been discussed in relation to impostor phenomenon and psychological functioning, indicating that burnout experiences may emerge in contexts where individuals face persistent performance pressure and self-evaluative concerns (Ojeda, 2024). In digital environments, similar pressure may be intensified through constant availability, comparison, multitasking, and digital performance expectations. Therefore, identifying high-risk digital burnout profiles based on technostress, online boundary control, and sleep procrastination can contribute to more targeted psychological, educational, and workplace interventions.

Taken together, previous research indicates that technostress reflects the stress burden of digital technology use, online boundary control reflects the capacity to regulate the intrusiveness of digital demands, and sleep procrastination reflects a behavioral pathway through which digital engagement may reduce recovery. These constructs are theoretically interconnected and empirically supported across studies of digital work, smartphone use, sleep quality, procrastination, and psychological well-being. However, the simultaneous use of these predictors in a machine learning classification framework remains limited. A CatBoost-based approach can extend prior research by moving beyond association testing and examining whether these variables can accurately classify digital burnout severity. Such an approach is especially relevant in Canadian digital users, whose daily life may involve high levels of online work, study, communication, and entertainment. By integrating psychological stress, boundary regulation, and sleep-related self-regulation into one predictive model, the present study addresses an important gap in digital mental health research.

The aim of this study was to classify digital burnout severity among adult digital technology users in Canada using the CatBoost machine learning algorithm based on technostress, online boundary control, and sleep procrastination.

2. Methods and Materials

2.1. *Study Design and Participants*

This study was conducted using a quantitative, applied, cross-sectional, and predictive classification design. The main objective of the study was to classify levels of digital burnout through the CatBoost machine learning algorithm based on technostress, online boundary control, and sleep procrastination. The statistical population consisted of adult digital technology users living in Canada who regularly used online platforms, digital communication tools, learning management systems, or work-related digital applications in their daily academic, occupational, or personal activities. The final sample included 486 participants from Canada. Participants were selected through convenience sampling using online recruitment procedures. Inclusion criteria were being 18 years of age or older, residing in Canada at the time of data collection, having regular daily use of digital devices and online communication platforms, and providing informed consent to participate in the study. Participants who submitted incomplete questionnaires, gave uniform responses across most items, or completed the survey in an unrealistically short time were excluded from the final analysis. Data were collected anonymously through an online questionnaire, and participants were informed that their participation was voluntary, their responses would remain confidential, and they could withdraw from the study at any stage before submitting the final form. The outcome

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variable of the study was digital burnout, which was converted into categorical classes for machine learning classification. Technostress, online boundary control, and sleep procrastination were considered predictor variables.

2.2. Measures

Digital burnout was measured using the Digital Burnout Scale developed by Erten and Özdemir. This instrument evaluates burnout symptoms associated with intensive and prolonged digital technology use and reflects the psychological, emotional, and behavioral fatigue that may emerge from continuous exposure to digital environments. The scale consists of 24 items and includes three dimensions: digital aging, digital deprivation, and emotional exhaustion. Items are scored on a Likert-type response format, with higher scores indicating higher levels of digital burnout. In the present study, the total digital burnout score was used to determine the target classification variable. For this purpose, participants' digital burnout scores were categorized into low, moderate, and high burnout groups based on the distribution of scores in the sample. The scale has been reported in previous studies to have acceptable construct validity and internal consistency, and in the present study its reliability was re-examined using Cronbach's alpha coefficient before conducting the main analysis.

Technostress was assessed using the Technostress Creators Scale developed by Tarafdar and colleagues and later validated in organizational and technology-use contexts. This instrument measures stress arising from the use of information and communication technologies. The scale includes five major dimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Techno-overload refers to the pressure to work faster or handle more tasks because of digital technologies; techno-invasion refers to the intrusion of technology into private and non-work time; techno-complexity reflects the perceived difficulty of understanding and using digital systems; techno-insecurity refers to concerns that one's technological skills are inadequate or replaceable; and techno-uncertainty refers to stress caused by frequent changes and updates in digital tools. Items are scored on a Likert-type scale, with higher scores representing greater technostress. In this study, both the total score and dimensional scores were used as predictive features in the CatBoost classification model.

Online boundary control was measured using a self-report scale adapted from work–nonwork boundary management and perceived boundary control measures. This tool assesses the degree to which individuals perceive that they can regulate the timing, frequency, and intrusiveness of online communication, digital notifications, and technology-mediated demands across personal, academic, and occupational domains. The construct reflects participants' perceived ability to separate online obligations from private life, manage availability expectations, control digital interruptions, and maintain psychological distance from online demands when needed. Items are rated on a Likert-type scale, with higher scores indicating stronger perceived control over online boundaries. In the current study, online boundary control was treated as a protective predictor, because greater perceived control over digital boundaries was theoretically expected to reduce the probability of belonging to the high digital burnout class.

Sleep procrastination was measured using the Bedtime Procrastination Scale developed by Kroese and colleagues. This scale evaluates the tendency to delay going to bed without external reasons preventing sleep. The instrument consists of nine items rated on a five-point Likert scale ranging from low frequency to high frequency of bedtime delay behaviors. Some items are reverse-scored, and the total score is calculated after correcting the reverse items. Higher scores indicate greater sleep procrastination and weaker self-regulation around bedtime. In the present study, sleep procrastination was included as a behavioral predictor of digital burnout because delayed sleep, especially when associated with late-night technology use, may intensify emotional exhaustion, reduce recovery time, and increase vulnerability to digital fatigue. The internal consistency of the scale was evaluated in the present sample using Cronbach's alpha.

2.3. Data analysis

Data analysis was conducted in several stages. First, the dataset was screened for incomplete responses, duplicated entries, outliers, careless response patterns, and impossible values. Missing data were examined, and cases with extensive missing responses were removed from the dataset. For cases with minimal missingness, appropriate imputation procedures were applied based on the distributional characteristics of the variables. Descriptive statistics, including mean, standard deviation, minimum, maximum, skewness, and kurtosis, were calculated for the main study variables. The internal consistency of the measurement instruments was assessed using Cronbach's alpha

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coefficient. Before developing the classification model, the digital burnout total score was transformed into three categorical classes representing low, moderate, and high digital burnout. This categorical outcome served as the dependent variable in the CatBoost classification model.

The predictive analysis was performed using the CatBoost classifier, a gradient boosting algorithm based on decision trees that is particularly suitable for structured data and can effectively model nonlinear relationships and complex interactions among predictors. The predictor variables included total and dimensional scores of technostress, online boundary control, and sleep procrastination. The dataset was divided into training and testing subsets, with 80% of the data used for model training and 20% reserved for model testing. To reduce the risk of overfitting and improve generalizability, cross-validation was applied within the training set. Model hyperparameters, including learning rate, tree depth, number of iterations, regularization strength, and class-weighting parameters, were tuned through validation procedures. Because digital burnout classes may not be equally distributed, class balance was examined and, where necessary, class-weight adjustment was applied to prevent the model from becoming biased toward the majority class.

Model performance was evaluated using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve. The confusion matrix was also examined to determine how accurately the model classified participants into low, moderate, and high digital burnout groups. Because the correct identification of high digital burnout was considered especially important, recall and F1-score for the high-burnout class were interpreted with particular attention. Feature importance values generated by the CatBoost model were used to identify the relative contribution of technostress, online boundary control, and sleep procrastination in the classification of digital burnout. Higher feature importance values indicated stronger predictive relevance in distinguishing burnout classes. All analyses were conducted using Python and relevant statistical and machine learning libraries. The level of statistical significance for preliminary statistical analyses was set at 0.05.

3. Findings and Results

The final analysis was conducted on data obtained from 486 adult digital technology users residing in Canada. The participants ranged in age from 18 to 59 years, with a mean age of 31.84 years and a standard deviation of 8.76 years. In terms of gender distribution, 281 participants were women, representing 57.82% of the sample, 195 participants were men, representing 40.12%, and 10 participants, representing 2.06%, identified as non-binary or preferred not to report their gender. Regarding educational status, 96 participants had a high school diploma or equivalent qualification, 173 had an undergraduate degree or were undergraduate students, 154 had a master’s degree or were enrolled in postgraduate education, and 63 had doctoral-level education or professional training. In relation to occupational status, 218 participants were employed full-time, 94 were employed part-time, 111 were university or college students, 38 were self-employed, and 25 were unemployed at the time of data collection. The average daily use of digital devices for occupational, academic, social, and recreational purposes was 7.42 hours, with a standard deviation of 2.31 hours. Most participants reported using digital technologies not only for communication and entertainment but also for work, study, administrative tasks, and online information seeking. Based on the categorized digital burnout scores, 159 participants were classified in the low digital burnout group, 194 in the moderate digital burnout group, and 133 in the high digital burnout group, indicating that a substantial proportion of the sample experienced at least moderate symptoms of digital fatigue, psychological exhaustion, and reduced recovery from digital engagement.

Table 1

Descriptive Statistics, Reliability Coefficients, and Correlations among the Main Study Variables

Variable	M	SD	Min	Max	Cronbach’s α	1	2	3	4
1. Digital burnout	72.36	14.82	31.00	112.00	0.91	1.00			
2. Technostress	68.44	13.57	29.00	105.00	0.89	0.61**	1.00		
3. Online boundary control	39.18	8.96	16.00	60.00	0.86	-0.43**	-0.37**	1.00	
4. Sleep procrastination	31.27	7.41	11.00	45.00	0.84	0.52**	0.45**	-0.31**	1.00

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As shown in Table 1, all measurement instruments demonstrated satisfactory internal consistency, with Cronbach's alpha coefficients ranging from 0.84 to 0.91. The highest reliability coefficient was observed for digital burnout, indicating strong internal consistency for the outcome variable. The descriptive results showed that participants had a moderate-to-high mean level of digital burnout, suggesting that digital fatigue and emotional exhaustion associated with technology use were meaningfully present in the sample. The correlation matrix also demonstrated theoretically consistent associations among the variables. Digital burnout had a strong positive correlation with technostress, indicating that participants who experienced higher levels of pressure, invasion, complexity, insecurity, and uncertainty related to digital technologies were more likely to report higher burnout symptoms. Digital burnout was also positively correlated with sleep procrastination, showing that individuals who delayed bedtime more frequently tended to experience greater digital exhaustion. In contrast, online boundary control had a significant negative correlation with digital burnout, indicating that participants who were better able to regulate digital availability, manage online interruptions, and separate personal time from digital demands reported lower levels of burnout. The negative association between online boundary control and technostress further suggests that weaker boundary regulation may intensify perceived technological pressure. Overall, the descriptive and correlational findings supported the suitability of technostress, online boundary control, and sleep procrastination as predictors in the CatBoost classification model.

Table 2

Classification Performance of the CatBoost Model for Digital Burnout Classes

Digital burnout class	Precision	Recall	F1-score	ROC-AUC
Low digital burnout	0.88	0.91	0.89	0.94
Moderate digital burnout	0.79	0.79	0.79	0.88
High digital burnout	0.84	0.81	0.82	0.91
Macro average	0.84	0.84	0.84	0.91
Weighted average	0.84	0.84	0.84	0.91
Overall accuracy			0.84	
Cohen's kappa			0.75	

Table 2 presents the predictive performance of the CatBoost classification model in distinguishing participants with low, moderate, and high digital burnout. The model achieved an overall accuracy of 0.84, indicating that 84% of participants in the test set were correctly classified into their respective burnout categories. The weighted F1-score was also 0.84, showing that the model maintained balanced predictive performance across the three outcome classes despite differences in class frequency. The strongest performance was observed for the low digital burnout class, with a precision of 0.88, recall of 0.91, and F1-score of 0.89. This result indicates that the model was particularly effective in identifying participants with relatively low burnout symptoms. For the moderate digital burnout group, the model produced a precision and recall of 0.79, suggesting that this class was the most difficult to distinguish, which is expected because moderate burnout may share characteristics with both low and high burnout profiles. The high digital burnout class showed strong classification performance, with a precision of 0.84, recall of 0.81, and F1-score of 0.82. The recall value for this class indicates that the model successfully identified most participants with high digital burnout, which is especially important from a psychological screening and prevention perspective. The macro-average ROC-AUC value of 0.91 further confirmed that the CatBoost model had strong discriminative capacity across all burnout categories. Cohen's kappa coefficient was 0.75, indicating substantial agreement between the predicted and observed digital burnout classifications beyond chance. Overall, these results demonstrate that the combination of technostress, online boundary control, and sleep procrastination provided a strong predictive basis for classifying digital burnout severity.

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Table 3

Confusion Matrix of the CatBoost Model on the Test Datasets

Actual class	Predicted low burnout	Predicted moderate burnout	Predicted high burnout	Total
Low digital burnout	29	3	0	32
Moderate digital burnout	4	31	4	39
High digital burnout	0	5	21	26
Total	33	39	25	97

Table 3 displays the confusion matrix for the CatBoost model on the independent test dataset. Out of 97 participants in the test set, 81 were correctly classified, corresponding to the overall accuracy reported in Table 2. Among participants who actually belonged to the low digital burnout class, 29 were correctly classified as low burnout, while only 3 were misclassified as moderate burnout and none were misclassified as high burnout. This finding indicates that the model rarely confused low burnout with high burnout, suggesting clear separation between individuals with low digital exhaustion and those with severe burnout symptoms. Among participants in the moderate burnout class, 31 were correctly classified, whereas 4 were incorrectly classified as low burnout and 4 as high burnout. This pattern confirms that the moderate group was located between the two extreme classes and therefore had greater overlap with adjacent burnout categories. Among participants with high digital burnout, 21 were correctly classified, while 5 were classified as moderate burnout and none were classified as low burnout. This result is important because it shows that the model did not mistakenly classify any high-burnout participant as low burnout, reducing the likelihood of overlooking individuals with more serious digital exhaustion. The main classification errors occurred between neighboring classes, particularly between moderate and high burnout, rather than between low and high burnout. This pattern supports the conceptual validity of the classification model, because digital burnout severity is expected to exist on a continuum rather than as completely isolated categories.

Figure 1

Relative Feature Importance of Technostress, Sleep Procrastination, and Online Boundary Control in the CatBoost Classification Model

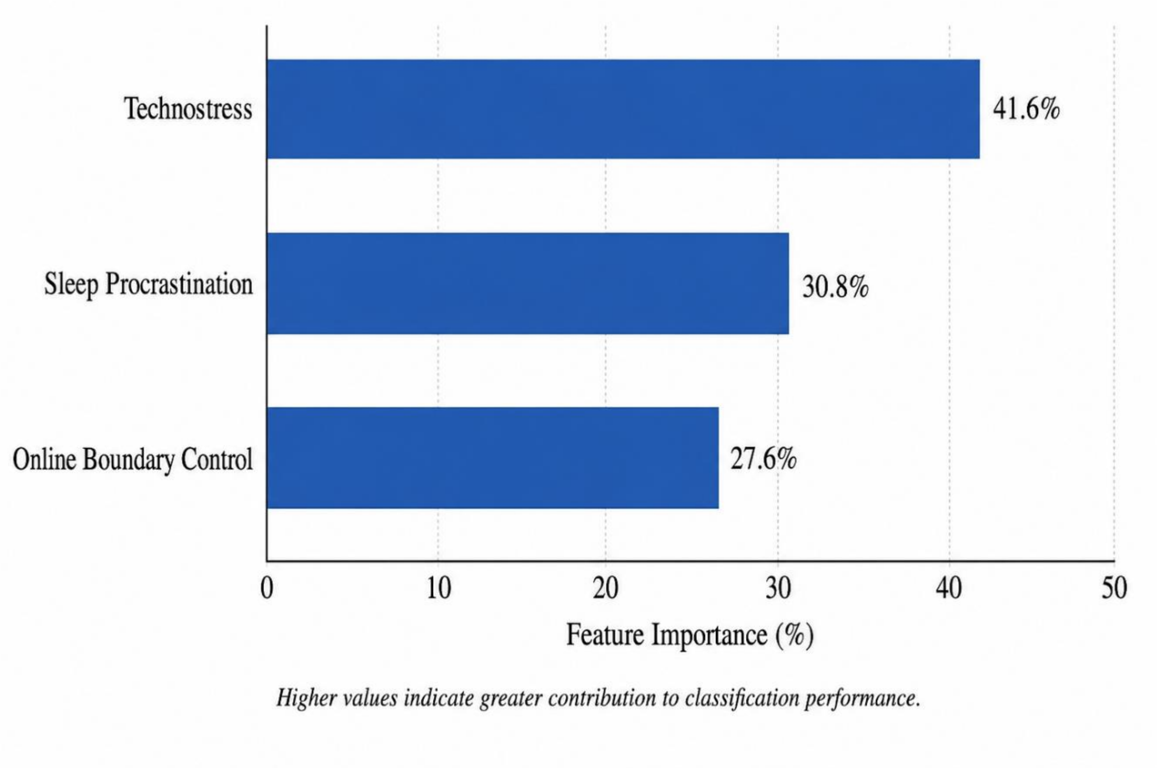

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Figure 1 illustrates the relative importance of the predictor variables in the CatBoost classification of digital burnout. The feature importance results showed that technostress made the largest contribution to the model, accounting for 41.60% of the total predictive importance. This indicates that stressors directly related to digital technology use, including overload, invasion, complexity, insecurity, and uncertainty, were the strongest indicators of whether participants belonged to the low, moderate, or high digital burnout groups. Sleep procrastination was the second most important predictor, accounting for 30.80% of the model's predictive structure. This result suggests that delayed bedtime behavior and reduced self-regulation around sleep were strongly associated with higher digital burnout classification, likely because sleep postponement reduces psychological recovery and increases vulnerability to fatigue caused by prolonged digital engagement. Online boundary control contributed 27.60% of the total feature importance and functioned as a protective predictor in the model. Participants with stronger perceived control over online availability, digital interruptions, and separation between personal and digital obligations were less likely to be classified in the high burnout group. Taken together, the feature importance pattern indicates that digital burnout is best explained by the combined effect of technological pressure, behavioral self-regulation around sleep, and the ability to manage boundaries in online environments. The CatBoost model therefore not only demonstrated satisfactory classification performance but also provided interpretable evidence regarding the psychological and behavioral mechanisms most relevant to digital burnout.

4. Discussion

The present study aimed to classify digital burnout among adult digital technology users in Canada using a CatBoost machine learning model based on technostress, online boundary control, and sleep procrastination. The findings showed that the model achieved strong classification performance, with an overall accuracy of 0.84, a weighted F1-score of 0.84, a macro-average ROC-AUC of 0.91, and a Cohen's kappa coefficient of 0.75. These indices indicate that the model had substantial ability to distinguish between low, moderate, and high levels of digital burnout. The strongest classification performance was observed for the low digital burnout group, while the moderate burnout group was comparatively more difficult to distinguish from adjacent categories. This pattern is conceptually reasonable because moderate burnout represents an intermediate condition that may share features with both low and high burnout profiles. The confusion matrix further showed that classification errors occurred mainly between neighboring classes and that no participant with high digital burnout was misclassified as low burnout. This finding is important because it suggests that the model was able to preserve meaningful separation between severe and minimal digital burnout conditions. Overall, the results support the usefulness of machine learning classification for identifying digital burnout profiles from psychological and behavioral predictors, especially when burnout is understood as a multidimensional condition shaped by technology-related stress, boundary disruption, and impaired recovery.

The descriptive and correlational findings also supported the theoretical foundation of the model. Digital burnout was positively correlated with technostress and sleep procrastination and negatively correlated with online boundary control. These associations indicate that digital burnout was higher among individuals who experienced stronger technology-related pressure, delayed sleep more frequently, and had weaker perceived control over online availability and digital intrusions. This pattern is consistent with the conceptualization of digital burnout as an exhaustion state arising from sustained exposure to digital demands without sufficient boundary regulation or recovery. The reliability coefficients of the main instruments were satisfactory, supporting the internal consistency of the measures used in the classification model. The observed association between technostress and digital burnout aligns with research showing that technology-mediated overload, invasion, complexity, uncertainty, and constant adaptation can intensify burnout experiences in digital work and academic contexts (Marrinhas et al., 2023). It also corresponds with broader occupational health psychology perspectives that consider technology-related stressors as emerging challenges for psychological well-being in contemporary work environments (Sarfraz et al., 2022). Therefore, the present findings confirm that digital burnout is not simply a consequence of frequent technology use, but rather a response to the stressful quality of technology-mediated demands.

Feature importance analysis showed that technostress was the strongest predictor in the CatBoost model, accounting for 41.60% of total predictive importance. This result indicates that technostress was the most influential variable in distinguishing digital burnout classes. The finding is theoretically expected because technostress directly reflects the pressure, intrusion, cognitive burden, and uncertainty associated with digital technology use. In online work and learning environments, individuals may experience pressure to respond rapidly, adapt to new platforms, manage continuous notifications, and perform multiple digital tasks simultaneously. When such demands accumulate, they can generate emotional exhaustion and cognitive fatigue, which are central features of burnout. This result is consistent with research on techno-social stress indicating that digital platforms and social network sites can produce stress through continuous interaction, comparison, information overload, and digital social pressure (Naga & Ebardo, 2025). It is also aligned with practical discussions of work–life balance in online contexts, which emphasize that technostress must be actively managed through boundary setting, digital communication control, and healthier technology-use routines (Clark, 2025). From this perspective, technostress functions as a proximal risk factor for digital burnout because it captures the subjective burden generated by technology rather than only the amount of time spent using devices.

The strong predictive role of technostress can also be interpreted through the changing structure of digital work. Contemporary work and education increasingly rely on virtual platforms, remote collaboration, online meetings, and asynchronous communication. Although these systems may improve flexibility, they can also create role overload, fragmented attention, and continuous connectivity when not supported by healthy work design. The SMART work design approach emphasizes that virtual work should support autonomy, manageable demands, relational connection, and tolerable levels of technological complexity (Wang & Parker, 2023). The current finding suggests that when digital work conditions are experienced as stressful and intrusive, the risk of digital burnout increases substantially. This interpretation is also consistent with evidence that social media and online communication influence well-being across work, home, and transitional spaces, showing that digital stress does not remain confined to one domain of life (Klingelhoefer & Meier, 2023). Therefore, technostress may contribute to digital burnout by carrying work-related, academic, or social demands into private time and by preventing psychological disengagement from digital obligations.

Sleep procrastination was the second most important predictor in the classification model, accounting for 30.80% of feature importance. This finding shows that delayed bedtime behavior had a substantial role in distinguishing participants with different levels of digital burnout. The positive correlation between sleep procrastination and digital burnout suggests that individuals who postpone sleep more frequently are more likely to experience digital fatigue and emotional exhaustion. This result is consistent with studies showing that bedtime procrastination is associated with problematic smartphone use and poor sleep quality (Bozkurt et al., 2024; Correa-Iriarte et al., 2023). It also aligns with research indicating that smartphone addiction and problematic digital engagement can contribute to bed procrastination and related behavioral difficulties, especially among adolescents and young users (Caninsti & Rahayu, 2024). The present study extends these findings by showing that sleep procrastination is not only related to sleep outcomes, but also contributes meaningfully to the classification of digital burnout severity.

The role of sleep procrastination in digital burnout can be explained through impaired recovery. Digital burnout reflects a condition in which the individual remains psychologically and behaviorally engaged with digital demands without adequate restoration. Sleep is one of the most essential mechanisms of recovery, and bedtime delay may reduce the opportunity for emotional regulation, cognitive restoration, and stress recovery. Research has shown that postponing sleep after stressful days is associated with poorer sleep outcomes, suggesting that stress and bedtime procrastination may form a maladaptive cycle (Schmidt et al., 2023). Insomnia severity has also been linked to bedtime procrastination, with emotion regulation strategies moderating this relationship, indicating that pre-sleep delay may be intensified when individuals struggle to regulate emotional arousal (Jeon et al., 2023). These findings support the interpretation that sleep procrastination may amplify digital burnout by reducing recovery from daily digital pressure. In addition, research on sleep disturbances and psychological well-being has emphasized the importance of sleep for mental health and resilience (Bahmani et al., 2024; Kamene, 2025). Therefore, individuals who frequently delay sleep after prolonged technology use may be especially vulnerable to burnout because they experience both elevated digital demand and reduced physiological and psychological restoration.

The association between sleep procrastination and digital burnout is further supported by studies linking mobile phone dependency, problematic internet use, fear of missing out, and sleep-related outcomes. Research among college students during the COVID-19 outbreak showed that bedtime procrastination and fear of missing out mediated the

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relationship between mobile phone dependency and sleep quality (Huang et al., 2023). Similarly, loneliness has been associated with interpersonal sensitivity through problematic internet use and bedtime procrastination among nursing undergraduates, suggesting that digital behaviors, emotional vulnerability, and sleep delay may be interconnected (Shi et al., 2024). Other research has emphasized the need for psychological prevention strategies for sleep procrastination among university students, particularly in demanding educational contexts (Jiang et al., 2024). These studies support the present finding that sleep procrastination is a meaningful behavioral marker of digital burnout risk. When individuals remain digitally engaged late into the night, bedtime delay may become a behavioral pathway through which technology use affects emotional exhaustion, attention regulation, and daily functioning.

The third predictor, online boundary control, contributed 27.60% of the total feature importance and was negatively correlated with digital burnout. This finding indicates that stronger perceived control over online availability, notifications, digital interruptions, and separation between personal and digital obligations was associated with lower burnout risk. Although its feature importance was lower than technostress and sleep procrastination, online boundary control still made a substantial contribution to classification. This result is consistent with the idea that digital burnout develops not only from the presence of technology-related demands but also from the individual's ability or inability to regulate those demands. Off-time work-related smartphone use has been associated with bedtime procrastination, showing that weak boundaries around work-related digital communication may extend occupational demands into sleep time (Hu et al., 2022). Similarly, research on focus, time management, and personal energy during online education highlights the importance of self-organization and boundary regulation in digitally mediated environments (Grah & Penger, 2022). The present findings suggest that online boundary control may operate as a protective factor by helping individuals preserve recovery time, reduce interruptions, and limit the psychological spillover of online demands.

The importance of online boundary control also helps explain why digital burnout should be examined as a multidimensional phenomenon. Individuals may experience high levels of technology use without severe burnout if they have sufficient control over when, how, and why they use digital tools. Conversely, even moderate technology use may become exhausting when it is experienced as uncontrollable, intrusive, or difficult to terminate. This interpretation is consistent with research showing that problematic smartphone use and sleep problems are shaped by psychological mechanisms such as compensatory health beliefs and bedtime procrastination (An & Zhang, 2024). Individuals may continue using digital technologies despite fatigue if they rationalize delayed rest or believe that recovery can be postponed. Procrastination theory also supports this explanation, as delay behavior is influenced by immediate reward, impulsiveness, expectancy, and temporal distance (Bok et al., 2024). In the digital context, immediate rewards from messages, social media, entertainment, or task completion can override the delayed benefits of sleep and recovery. Conceptual work on procrastination in professional contexts similarly suggests that delay is not merely poor time management but a self-regulatory process influenced by motivation, stress, and context (Mai et al., 2025).

The present results also correspond with studies linking procrastination, smartphone use, self-control, and health-related routines. Network analysis has shown connections between problematic smartphone use, exercise procrastination, and self-control, indicating that digital behavior and procrastination may be part of a broader self-regulation system (He et al., 2025). Research on physical exercise and bedtime procrastination among college students has also highlighted the mediating roles of self-control and mobile phone addiction, suggesting that digital dependence can interfere with adaptive routines (Wang et al., 2025). Longitudinal evidence has further linked mobile phone addiction, bedtime procrastination, and campus-based physical activity, showing that digital habits may shape health behaviors over time (Deng & Li, 2025). These findings align with the present study by suggesting that digital burnout risk is not isolated from broader patterns of self-regulation. Rather, individuals who struggle with digital boundaries and bedtime delay may also experience reduced capacity to maintain healthy routines, regulate attention, and recover from daily stress.

The classification results are also meaningful in light of broader evidence on problematic digital behavior and well-being. Boredom proneness has been linked to phubbing through self-control and bedtime procrastination, suggesting that emotional states and regulatory capacities may influence compulsive or habitual digital engagement (Meng & Xuan, 2023). Research on digital devices and adolescent sleep has similarly emphasized that screen-based habits are relevant to sleep health, although the mechanisms may differ across age

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groups and contexts (Fiore et al., 2025). Other studies have examined how bedtime procrastination relates to thought control, lockdown experiences, and daily routines, further supporting the idea that sleep delay is embedded in cognitive and environmental conditions (Oliveira et al., 2022; Roy et al., 2022). Even studies addressing sleep quality in relation to media and cultural habits point to the broader role of lifestyle and digital routines in shaping rest and well-being (Sadjiarto & Susilo, 2024). The present findings add to this literature by showing that the combined pattern of technostress, online boundary control, and sleep procrastination can classify digital burnout with strong accuracy.

5. Conclusion

Although the strongest emphasis of the present model was on digital stress and sleep-related behavior, the findings also have implications for broader burnout and well-being research. Burnout has been examined in relation to psychological vulnerability and performance-related pressure, including the impostor phenomenon (Ojeda, 2024). In digital environments, comparable pressures may arise through constant comparison, visibility, productivity expectations, and responsiveness norms. The present study suggests that digital burnout may be better understood when personal self-regulation and environmental digital demands are examined together. Emerging work on exercise procrastination and exercise addiction from socio-ecological perspectives also supports the value of considering individual behavior within broader environmental and contextual systems (Wang, 2026). Similarly, temporal network evidence linking bedtime procrastination and depression among adolescents indicates that procrastination-related sleep behavior may interact dynamically with mental health symptoms across time (Gao et al., 2026). Taken together, these studies support the conclusion that digital burnout should be investigated as a complex phenomenon involving stress exposure, boundary control, behavioral delay, and recovery processes.

6. Limitations & Suggestions

The present study had several limitations. First, the cross-sectional design prevents causal interpretation of the relationships among technostress, online boundary control, sleep procrastination, and digital burnout. Although the CatBoost model classified digital burnout with strong accuracy, it cannot determine whether technostress and sleep procrastination cause burnout or whether individuals experiencing burnout become more vulnerable to stress and bedtime delay. Second, the study relied on self-report questionnaires, which may be affected by response bias, social desirability, recall limitations, and subjective interpretation of item content. Third, the sample consisted of adult digital technology users in Canada recruited through convenience sampling, which limits the generalizability of the findings to other populations, countries, occupational groups, or individuals with limited digital access. Fourth, digital burnout was categorized into low, moderate, and high classes based on score distribution, and different classification thresholds may produce somewhat different model results. Finally, although the model included theoretically important predictors, other relevant variables such as personality traits, work demands, social support, digital literacy, emotional regulation, physical activity, and mental health symptoms were not included.

Future studies should use longitudinal designs to examine how technostress, boundary control, sleep procrastination, and digital burnout influence one another over time. Repeated-measures and daily diary designs would be particularly useful for identifying short-term fluctuations in digital demands, evening technology use, bedtime delay, sleep quality, and next-day exhaustion. Future research should also compare CatBoost with other machine learning algorithms, such as random forest, support vector machines, XGBoost, LightGBM, and neural network models, to determine whether different modeling approaches produce similar classification performance. In addition, future studies should test the model in more diverse samples, including remote workers, university students, healthcare workers, teachers, adolescents, and older adults. It would also be useful to include objective indicators such as screen-time logs, notification frequency, sleep tracking data, and app-use patterns to supplement self-report measures. Finally, future research should examine whether online boundary control moderates the effects of technostress and sleep procrastination on digital burnout, because individuals with stronger boundary regulation may be more resilient even when digital demands are high.

The practical findings of this study suggest that digital burnout prevention should focus on reducing technostress, strengthening online boundary control, and improving sleep-related self-regulation. Workplaces, universities, and digital service environments should develop clear expectations around response time, after-hours availability, notification norms, and platform use. Individuals should be encouraged

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to establish technology-free recovery periods, reduce unnecessary notifications, separate work-related and personal digital spaces, and develop consistent bedtime routines. Interventions should also address the psychological tendency to delay sleep through late-night digital engagement by promoting self-monitoring, implementation intentions, and healthier evening habits. Because the model showed that high digital burnout could be identified with strong accuracy, screening programs may use brief assessments of technostress, boundary control, and sleep procrastination to detect individuals at risk before more severe exhaustion develops. In practical settings, digital well-being programs should not focus only on reducing screen time; instead, they should help individuals improve the quality, timing, controllability, and recovery balance of their digital lives.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed in this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

References

An, Y., & Zhang, M. X. (2024). Relationship Between Problematic Smartphone Use and Sleep Problems: The Roles of Sleep-Related Compensatory Health Beliefs and Bedtime Procrastination. *Digital Health*, *10*. https://doi.org/10.1177/20552076241283338

Bahmani, D. S., Rigotti, V., Stanga, Z., Lang, U. E., Blais, R. K., Kelley, M. L., & Brand, S. (2024). Sleep Disturbances and Psychological Well-Being Among Military Medical Doctors of the Swiss Armed Forces: Study Protocol, Rationale and Development of a Cross-Sectional and Longitudinal Interventional Study. *Frontiers in Public Health*, *12*. https://doi.org/10.3389/fpubh.2024.1390636

Bok, S., Shum, J., & Lee, M. (2024). Temporal Motivation Theory: Punctuality Is a Matter of Seconds. *Journal of Marketing Education*, *46*(3), 225-239. https://doi.org/10.1177/02734753241232564

Bozkurt, A., Demirdöğen, E. Y., & Akıncı, M. A. (2024). The Association Between Bedtime Procrastination, Sleep Quality, and Problematic Smartphone Use in Adolescents: A Mediation Analysis. *Eurasian Journal of Medicine*, *56*(1), 69-75. https://doi.org/10.5152/eurasianjmed.2024.23379

Caninsti, R., & Rahayu, S. A. T. (2024). The Role of Smartphone Addiction on Bed Procrastination and Mindful Eating Behavior in Adolescents. *Indigenous Jurnal Ilmiah Psikologi*, *9*(1), 1-13. https://doi.org/10.23917/indigenous.v9i1.2804

Choi, S.-Y., & Kim, J.-H. (2024). Validity and Reliability of the Korean Version of the Digital Burnout Scale. *Frontiers in Public Health*, *12*. https://doi.org/10.3389/fpubh.2024.1386394

Clark, T. A. (2025). Work–Life Balance in an Online World: Simple Strategies for Managing Technostress. *Journal of Pediatric Surgical Nursing*, *14*(4), 132-138. https://doi.org/10.1177/23320249251367754

Correa-Iriarte, S., Hidalgo-Fuentes, S., & Vilar, M. M. (2023). Relationship Between Problematic Smartphone Use, Sleep Quality and Bedtime Procrastination: A Mediation Analysis. *Behavioral Sciences*, *13*(10), 839. https://doi.org/10.3390/bs13100839

Deng, M., & Li, Z. (2025). The Relationship Between Mobile Phone Addiction, Bedtime Procrastination, and Campus-Based Physical Activity: A Longitudinal Follow-Up Study Based on a College Student Population. *Frontiers in psychology*, *16*. https://doi.org/10.3389/fpsyg.2025.1690574

Fiore, M., Arena, D., Crisafi, V., Grieco, V., Palella, M., Timperanza, C., Conti, A., Cuffari, G., & Ferrante, M. (2025). Digital Devices Use and Sleep in Adolescents: An Umbrella Review. *International journal of environmental research and public health*, *22*(10), 1517. https://doi.org/10.3390/ijerph22101517

Gao, T., Zhang, W., & Su, Y. (2026). Temporal Network Analysis of Bedtime Procrastination and Depression Among Adolescents: A Prospective Longitudinal Study. *Medcomm*, *7*(2). https://doi.org/10.1002/mco2.70620

Grah, B., & Penger, S. (2022). Focus, Time Management and Personal Energy of Students During Online Education. *ENTRENOVA - ENTerprise REsearch InNOVAtion*, *8*(1), 127-137. https://doi.org/10.54820/entrenova-2022-0012

He, Y., Wen, J., Liu, F., Zhou, C., Qian, P., & Miao, M. (2025). Mapping the Links Between Problematic Smartphone Use, Exercise Procrastination, and Self-Control: A Network

Analysis. *BMC psychology*, *13*(1). https://doi.org/10.1186/s40359-025-03051-x

Hu, W., Ye, Z., & Zhang, Z. (2022). Off-Time Work-Related Smartphone Use and Bedtime Procrastination of Public Employees: A Cross-Cultural Study. *Frontiers in psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.850802

Huang, T., Liu, Y., Tan, T. C., Wang, D., Zheng, K., & Liu, W. (2023). Mobile Phone Dependency and Sleep Quality in College Students During COVID-19 Outbreak: The Mediating Role of Bedtime Procrastination and Fear of Missing Out. https://doi.org/10.21203/rs.3.rs-2497672/v1

Jeon, H., Lee, W. E., & Suh, S. (2023). Emotion Regulation Strategies as a Moderator Between Insomnia Severity and Bedtime Procrastination. *Sleep Medicine Research*, *14*(4), 220-226. https://doi.org/10.17241/smr.2023.02033

Jiang, X., Xie, L. Y., & Wang, S. (2024). Study on Sleep Procrastination Behavior and Psychological Prevention Strategies Among University Students During Vocational Awareness Internships. *Pacific International Journal*, *7*(4), 129-134. https://doi.org/10.55014/pij.v7i4.662

Kamene, K. (2025). Insomnia Epidemic: How Poor Sleeping Habits Are Undermining Mental Wellness. *Premier Journal of Social Science*. https://doi.org/10.70389/pjss.100012

Klingelhoefer, J., & Meier, A. (2023). Social Media and Well-Being at Work, at Home, and in-Between: A Review. 398-418. https://doi.org/10.4337/9781789906769.00032

Mai, X., Zhang, J., & Zhu, M. (2025). Procrastination Within the Nursing Context: A Concept Analysis. *Nursing Open*, *12*(10). https://doi.org/10.1002/nop2.70308

Marrinhas, D., Santos, V., Salvado, C., Pedrosa, D., & Pereira, A. (2023). Burnout and Technostress During the COVID-19 Pandemic: The Perception of Higher Education Teachers and Researchers. *Frontiers in Education*, *8*. https://doi.org/10.3389/feduc.2023.1144220

Meng, F., & Xuan, B. (2023). Boredom Proneness on Chinese College Students' Phubbing During the COVID-19 Outbreak: The Mediating Effects of Self-Control and Bedtime Procrastination. *Journal of Healthcare Engineering*, *2023*(1). https://doi.org/10.1155/2023/4134283

Naga, J. F., & Ebardo, R. (2025). Social Network Sites (SNS) an Archetype of Techno-Social Stress: A Systematic Review. *Heliyon*, *11*(1), e41119. https://doi.org/10.1016/j.heliyon.2024.e41119

Ojeda, L. (2024). Impostor Phenomenon and Burnout. 81-109. https://doi.org/10.1037/0000397-005

Oliveira, A., Pereira, B., Rosário, P., & Magalhães, P. (2022). Bedtime Procrastination During the Second COVID-19 Lockdown in Portugal. *Sleep Science*, *15*(01), 105-111. https://doi.org/10.5935/1984-0063.20220031

Roy, R. S., John, S. M. T., & John, J. M. (2022). Bedtime Procrastination and Thought Control Among Hostellers And Day Scholars. *International Journal of Engineering Technology and Management Sciences*, *6*(5), 498-504. https://doi.org/10.46647/ijetms.2022.v06i05.077

Sadjiarto, R. E. A. A. S. A., & Susilo, D. (2024). The Influence of Japanese City Pop Music on Emerging Adults' Sleep Quality. *Incoheliv*, *1*(1), 60-68. https://doi.org/10.24123/incoheliv.v1i1.6562

Sarfraz, M., Ivașcu, L., Shah, S. G. M., & Farid, A. (2022). Editorial: Cross-Cultural Occupational Health Psychology Challenges for the 21st Century. *Frontiers in psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.970631

Schmidt, L. I., Baetzner, A. S., Dreisbusch, M. I., Mertens, A., & Sieverding, M. (2023). Postponing Sleep After a Stressful Day: Patterns of Stress, Bedtime Procrastination, and Sleep Outcomes in a Daily Diary Approach. *Stress and Health*, *40*(3). https://doi.org/10.1002/smi.3330

Shi, X., Wu, Y., Cao, F., Wang, X., Du, K., & Zang, S. (2024). The Effect of Loneliness on Interpersonal Sensitivity Among Nursing Undergraduates: A Chain Mediation Role of Problematic Internet Use and Bedtime Procrastination. *BMC Nursing*, *23*(1). https://doi.org/10.1186/s12912-024-02321-0

Wang, B., & Parker, S. K. (2023). Embracing the Digital Workplace: A SMART Work Design Approach to Supporting Virtual Work. 403-424. https://doi.org/10.4337/9781802200508.00032

Wang, Y. (2026). Socio-Ecological Correlates of Exercise Procrastination and Exercise Addiction: A Preliminary Exploratory Study Using a Single-University Sample. *Frontiers in Psychiatry*, *17*. https://doi.org/10.3389/fpsyt.2026.1787438

Wang, Y. M., Wang, X., Wu, S., Zhang, W., Li, J., & Liu, B. (2025). Physical Exercise and Bedtime Procrastination Among College Students: Mediating Roles of Self-Control and Mobile Phone Addiction. *Frontiers in psychology*, *16*. https://doi.org/10.3389/fpsyg.2025.1630326

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