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Navigating Digital Distraction in Learning: The Role of Technology, Emotions, and Classroom Environment

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ABSTRACT: In today's technology-driven academic environments, digital distraction has become a critical challenge to student concentration and learning effectiveness. This study investigates the psychological, behavioral, and contextual factors influencing digital distraction among university students. Drawing on Cognitive Load Theory, Self-Regulation Theory, and Attention Control Theory, the study develops and tests a comprehensive structural model incorporating Technology Usage Frequency, Cognitive Load, Emotional State, Self-Regulation Ability, and Social Media Engagement, with the Classroom Environment as a moderator. Data were collected from 508 valid responses via an online survey and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that Technology Usage Frequency and Cognitive Load are key predictors of digital distraction, while Self-Regulation Ability serves as a protective factor. Emotional State and Social Media Engagement also contribute to distraction, although the link between social media and emotional state was not statistically significant. Furthermore, the Classroom Environment significantly moderates several relationships, amplifying or buffering their effects on distraction. The model explains 47.1% of the variance in digital distraction, offering strong empirical support for its explanatory power. The study provides theoretical insights into the interplay between internal and external influences on attention and delivers practical recommendations for designing distraction-resistant learning environments.

KEYWORDS: Digital distraction; Cognitive load; Self-regulation; Emotional state; Technology use; Social media engagement; Classroom environment.

1. INTRODUCTION

1.1. Research Context

In today's academic environment, digital devices have become integral to students' daily lives, offering both educational and non-educational benefits (Vázquez Cano & Sevillano-García, 2018; Dorris et al., 2021; Gurukkal, 2023). However, the constant presence of these devices has also introduced challenges, notably in the form of digital distractions (Pérez-Juárez et al., 2023). *Digital distraction* refers to the tendency of students to engage with digital devices for non-academic purposes during study or learning sessions (Simanjuntak et al., 2022), leading to interruptions in focus and reduced learning outcomes (Wang, 2022; Pérez-Juárez et al., 2023). In the context of higher education, this distraction has become a growing concern, as students often engage in multitasking behaviors, such as checking social media, browsing the internet, or playing games while attending classes or studying (Larry D. Rosen et al., 2013; Deng et al., 2019; Pérez-Juárez et al., 2023).

Numerous studies have highlighted the negative impacts of digital distractions on students' academic performance. For instance, frequent interruptions by digital devices can lead to fragmented attention (Liu & Gu, 2020), increased cognitive load (Skulmowski & Xu, 2022), and decreased retention of information (Lepp et al., 2014; Schmidt et al., 2022; Wang, 2022). As digital distractions become more prevalent, understanding the factors that contribute to students' susceptibility to these distractions is crucial for developing effective strategies to enhance academic engagement and focus.

Given the widespread use of technology in academic settings, it is essential to investigate how various factors, such as *Technology Usage Frequency*, *Cognitive Load*, *Emotional State*, and *Self-Regulation Ability*, interact to influence students' susceptibility to digital distraction. Additionally, the *Classroom Environment* may play a moderating role, either amplifying or reducing the impact of these factors on digital distraction. This study aims to address these aspects, providing a comprehensive understanding of the predictors of digital distraction in educational settings.

1.2. Research Gap

While digital distraction has been recognized as a significant issue in educational settings, much of the existing research has primarily focused on the prevalence and effects of digital distraction on academic performance (Hietajärvi et al., 2022; Liao & Wu, 2022; Zhao, 2023; Zhou & Deng, 2024). However, relatively few studies have examined the underlying factors that contribute to students' susceptibility to digital distraction, particularly the roles of *Cognitive Load*, *Emotional State*, and *Self-Regulation Ability*. Understanding these factors is crucial because they represent internal mechanisms that may influence a student's capacity to maintain focus in the presence of digital devices.

Moreover, while some studies have considered *Technology Usage Frequency* and *Social Media Engagement* as predictors of digital distraction (Siebers et al., 2022; Göl et al., 2023; Zhou & Deng, 2024), the interaction between these factors and students' cognitive and emotional states remains underexplored. Specifically, the dual impact of frequent technology use on increasing cognitive load and emotional strain has not been fully investigated, leaving a gap in understanding how these factors interact to exacerbate digital distraction.

Furthermore, the moderating role of the *Classroom Environment* - how structured and supportive educational settings might mitigate or amplify digital distraction - has received limited attention. Although some studies suggest that a well-regulated classroom environment can reduce the likelihood of digital distraction (Aagaard, 2022; Wang et al., 2022; Zhou & Deng, 2024), empirical evidence on its moderating effects across different psychological and behavioral factors is still sparse.

This study addresses these gaps by developing and testing a comprehensive model that includes *Technology Usage Frequency*, *Cognitive Load*, *Emotional State*, *Self-Regulation Ability*, and *Social Media Engagement* as predictors of digital distraction. Additionally, it examines the moderating influence of the *Classroom Environment* on these relationships, offering insights that extend the current understanding of digital distraction in educational contexts.

1.3. Research Objectives and Questions

This study aims to investigate the psychological, behavioral, and contextual factors influencing digital distraction among university students. Specifically, it explores how *Technology Usage Frequency*, *Cognitive Load*, *Emotional State*, *Self-Regulation Ability*, and *Social Media Engagement* Impact *Digital Distraction*, with the *Classroom Environment* as a potential moderator. Key research questions include: RO1: What factors directly influence digital distraction in educational settings? RO2: How do self-regulation and classroom environment shape these relationships?

1.4. Research Methodology Overview

This study employs the *Partial Least Squares Structural Equation Modeling* (PLS-SEM) method to analyze the relationships among the variables in the research model. PLS-SEM is a robust multivariate analysis technique particularly suitable for complex models with multiple constructs, as it allows for the simultaneous analysis of relationships between observed and latent variables (Joseph F Hair Jr et al., 2021). Unlike covariance-based SEM, PLS-SEM focuses on maximizing the explained variance of the dependent variables, making it an ideal choice for exploratory studies and theory development in emerging research areas like digital distraction.

SmartPLS software was chosen for data analysis due to its user-friendly interface, flexibility in handling complex models, and support for various statistical functions required in PLS-SEM, including moderation and mediation analysis (Ringle, 2015). This software also provides advanced visualization tools that facilitate the interpretation of results, making it a preferred option for researchers applying PLS-SEM in social sciences.

1.5. Structure of the Paper

The remainder of this paper is organized as follows: Section 2 provides a comprehensive literature review, focusing on digital distraction and its key predictors, including *Technology Usage Frequency*, *Cognitive Load*, *Emotional State*, *Self-Regulation Ability*, and *Social Media Engagement*. Section 3 describes the research methodology, detailing the data collection process, measurement scales, and analytical approach using PLS-SEM. Section 4 presents the study's results, including assessments of the measurement model, structural model, and moderation analysis. Section 5 discusses the key findings in relation to existing literature, theoretical implications, and practical recommendations for reducing digital distraction in educational contexts. Finally, Section 6 concludes the paper by summarizing the main contributions, acknowledging limitations, and suggesting avenues for future research.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Foundational theories

2.1.1. Cognitive Load Theory

Cognitive Load Theory (CLT) posits that an individual's working memory has limited capacity, and excessive cognitive demands can impair learning and task performance (Sweller et al., 2011b; Hossain & Yeasin, 2015; El Mansouri et al., 2024). CLT categorizes cognitive load into three types: intrinsic load (complexity of the task itself), extraneous load (inefficiencies in task presentation), and germane load (resources allocated to learning processes) (Sweller et al., 2011a). In the context of digital distraction, frequent task-switching due to digital devices increases the extraneous load, reducing students' capacity to focus on academic tasks effectively (Alho et al., 2022; Wang et al., 2023). This theory underpins the investigation of cognitive overload as a key driver of digital distraction in this study.

2.1.2. Self-Regulation Ability Theory

Self-regulation ability Theory emphasizes an individual's capacity to control attention, emotions, and behaviors to achieve long-term goals (Zimmerman, 2000; Junaštíková, 2024). Effective self-regulation is essential for managing distractions and maintaining focus in challenging environments, such as classrooms where digital devices are prevalent (Schunk & Zimmerman, 2012; Zimmerman, 2023). Students with stronger self-regulation abilities are better equipped to resist digital distractions and sustain attention on academic tasks (Ibrahim et al., 2024; Junaštíková, 2024). This theory provides a basis for examining self-regulation as both an outcome of cognitive load and a mediator of its effects on digital distraction.

2.1.3. Attention Control Theory (ACT)

Attention Control Theory (ACT) explores how stress and emotional states influence an individual's ability to allocate and sustain attention effectively (Eysenck et al., 2007; Wei & Sun, 2024). The theory posits that high-stress levels or negative emotions impair attention control, making individuals more susceptible to distractions (Wei & Sun, 2024). In educational settings, students experiencing anxiety or boredom are more likely to seek digital distractions as a coping mechanism, which further disrupts their focus (Göl et al., 2023; Zhang et al., 2023). ACT supports the exploration of emotional state and classroom environment as critical factors influencing digital distraction.

2.2. Key variables and hypotheses development

2.2.1. Technology Usage Frequency and Its Impact on Cognitive Load and Digital Distraction

Technology usage frequency refers to how often students engage with digital devices, such as smartphones, tablets, and computers, for both academic and non-academic purposes. Frequent technology usage has been associated with increased cognitive demands (Alho et al., 2022), as students must navigate and process multiple sources of information simultaneously, which can lead to cognitive overload (Small et al., 2020; Wang et al., 2023). Studies indicate that habitual technology use, especially for non-academic purposes, requires students to frequently switch between tasks (Uzun & Kilis, 2019; Alho et al., 2022), thereby increasing cognitive load as they manage competing demands for attention (Wilmer et al., 2017; Alho et al., 2022; Raj et al., 2023). Moreover, frequent engagement with digital devices has been linked to a higher likelihood of digital distraction (Benge et al., 2023). Students who regularly use technology may develop habitual checking behaviors, where they are drawn to check notifications, messages, or social media during academic tasks, which reduces their focus and learning efficiency (Wang et al., 2022; Zhou & Deng, 2024). Consequently, high levels of technology usage frequency increase cognitive load and make students more susceptible to digital distractions (Aagaard, 2021; Göl et al., 2023; Zhang et al., 2023). Based on these observations, we propose the following hypotheses:

H1a*: Technology Usage Frequency positively impacts Cognitive Load.*

H1b*: Technology Usage Frequency positively impacts Digital Distraction.*

2.2.2. Cognitive Load and Its Impact on Self-Regulation Ability and Digital Distraction

Cognitive load refers to the mental effort required to process and retain information. According to Cognitive Load Theory, high cognitive load can hinder information processing and decrease the ability to sustain attention to tasks (Sweller et al., 2011a). In academic settings, cognitive overload can impair students' ability to regulate their attention, making it difficult for them to stay focused (Alho et al., 2022; Wang et al., 2023).

Furthermore, cognitive load has been shown to increase digital distraction, as students experiencing high cognitive demands may seek relief through off-task digital activities (L. D. Rosen et al., 2013). This tendency to shift attention away from academic tasks can reduce learning effectiveness and lead to frequent interruptions. Therefore, we propose the following hypotheses:

H2a*: Cognitive Load negatively impacts Self-Regulation Ability.*

H2b*: Cognitive Load positively impacts Digital Distraction.*

2.2.3. Emotional State and Its Impact on Self-Regulation Ability and Digital Distraction

Emotional state plays a critical role in influencing students' attention and focus. Negative emotional states, such as stress, anxiety, or boredom, can diminish self-regulation ability, making it harder for students to control their focus on academic tasks (Pekrun et al., 2010). Negative emotions often drive students to seek digital distractions as a means of alleviating discomfort or avoiding academic challenges (Steinert & Dennis, 2022).

Students experiencing negative emotional states are, therefore, more likely to turn to digital distractions as a coping mechanism, further diminishing their academic engagement and focus. Thus, we propose:

***H4a**: Emotional State negatively impacts Self-Regulation Ability.*

***H4b**: Emotional State positively impacts Digital Distraction.*

2.2.4. Self-Regulation Ability and Its Impact on Digital Distraction

Self-regulation ability refers to a student's capacity to control attention and behavior in order to achieve academic goals. High self-regulation allows students to resist distractions and maintain focus even when digital devices are readily accessible (Zimmerman, 2000). Students with strong self-regulation skills are less likely to engage in non-academic digital activities, as they can effectively manage their impulses and stay focused on their studies (Zimmerman, 2002; Schunk & Zimmerman, 2012; Zimmerman, 2023). Accordingly, we propose:

***H3**: Self-Regulation Ability negatively impacts Digital Distraction.*

2.2.5. Social Media Engagement and Its Impact on Emotional State and Digital Distraction

Social media engagement is a significant predictor of emotional state and digital distraction. High levels of engagement with social media can exacerbate feelings of anxiety and FOMO (fear of missing out), leading to emotional strain (Przybylski et al., 2013). Social media engagement can also encourage students to turn to digital devices more frequently, increasing the likelihood of digital distraction during academic tasks (Larry D. Rosen et al., 2013). Thus, we propose:

***H5a**: Social Media Engagement positively impacts Emotional State.*

***H5b**: Social Media Engagement positively impacts Digital Distraction.*

2.2.6. Classroom Environment as a Moderator

The classroom environment can serve as a moderating factor, either amplifying or reducing the effects of various predictors on digital distraction (Bonnick, 2014). Structured classroom settings, with clear rules on device usage and interactive teaching methods, may help mitigate digital distraction by discouraging non-academic use of digital devices (Hanaysha et al., 2023). Conversely, permissive or unregulated classrooms may increase the likelihood of distraction, as students may feel free to engage with their devices (Fraser, 1998; Anshari et al., 2017). Therefore, we propose the following moderated hypotheses:

***H6a**: Classroom Environment moderates the relationship between Technology Usage Frequency and Digital Distraction.*

***H6b**: Classroom Environment moderates the relationship between Cognitive Load and Digital Distraction.*

***H6c**: Classroom Environment moderates the relationship between Emotional State and Digital Distraction.*

***H6d**: Classroom Environment moderates the relationship between Self-Regulation Ability and Digital Distraction.*

***H6e**: Classroom Environment moderates the relationship between Social Media Engagement and Digital Distraction.*

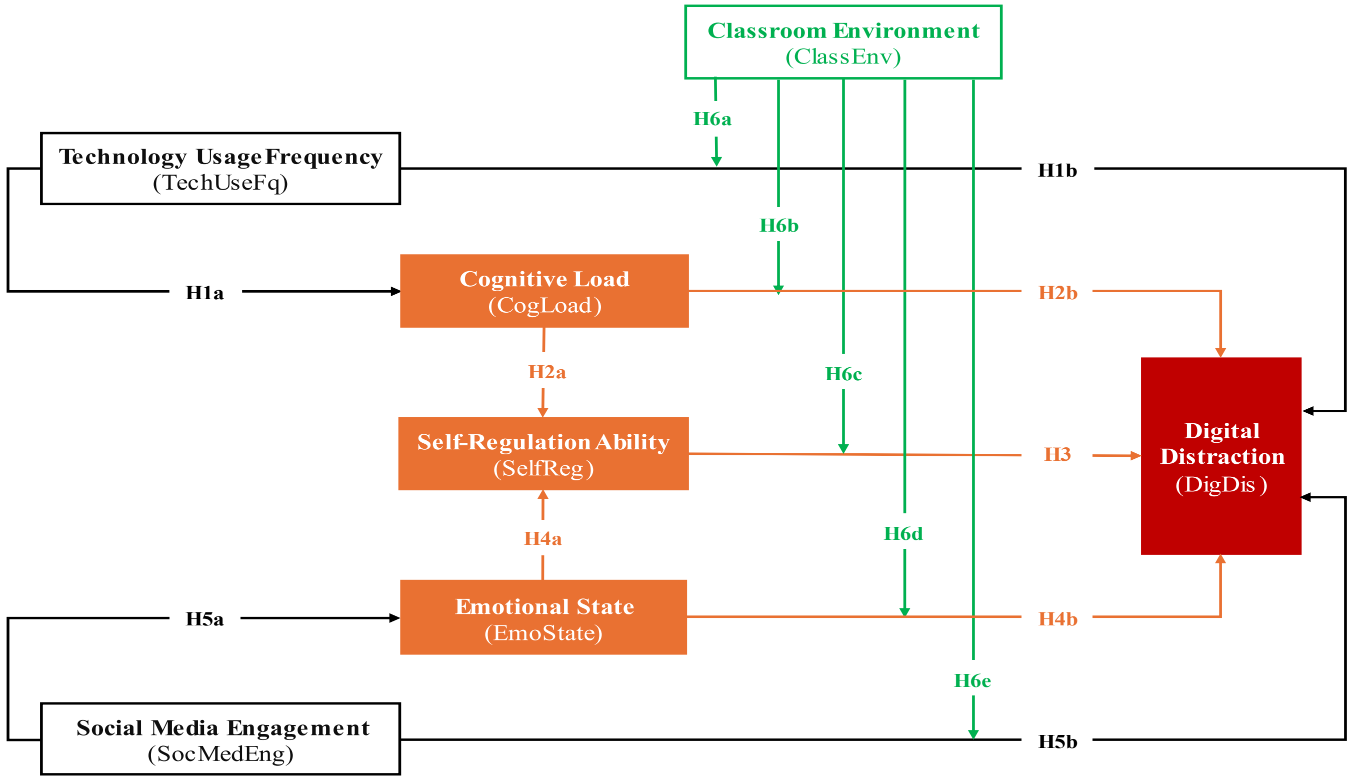

Figure 1. Conceptual model

3. METHODOLOGY

3.1. Research design

This study employed a mixed-methods research design to explore the factors influencing digital distraction among university students. The research process began with a qualitative phase, including interviews with five PhD students at the National Economics University (NEU), to refine the survey questionnaire and ensure the appropriateness of the measurement scales. Based on these insights, the survey was translated from English to Vietnamese and pre-tested in a pilot study with 70 university students to assess clarity and reliability. The final questionnaire utilized a 7-point Likert scale to capture responses ranging from 1 (strongly disagree) to 7 (strongly agree). The survey included measures for all variables in the research model, including *Technology Usage Frequency*, *Cognitive Load*, *Emotional State*, *Self-Regulation Ability*, *Social Media Engagement*, and *Digital Distraction*, as well as items for assessing the moderating variable, *Classroom Environment*.

3.2. Data Collection

Data were gathered through an online survey from June 2024 to September 2024 and distributed to university students. Participants were asked to voluntarily complete the survey, which took approximately 10-15 minutes. A total of 800 responses were collected, of which 508 were valid and used for analysis after data cleaning to remove incomplete or inconsistent responses. The sample included respondents from various age groups, educational levels, and gender identities, ensuring a comprehensive representation for analysis. Detailed demographic information is summarized in Table 1.

3.3. Measurement Scales

Each variable in the research model was measured using validated scales adapted from previous studies: Technology Usage Frequency: Measured by (Gamito et al., 2016), assessing students' daily engagement with digital devices for academic and non-academic purposes. Cognitive Load: Based on scales by Sweller et al. (2011b), measuring the perceived cognitive effort required during academic tasks. Emotional State: Measured using items adapted from Pekrun et al. (2010), covering feelings such as stress, anxiety, and boredom. Self-Regulation Ability: Adapted from Zimmerman (Zimmerman, 2000; Zimmerman, 2023), assessing students' capacity to manage their attention and impulses. Social Media Engagement: Adapted from (Przybylski et al., 2013), measuring frequency and intensity of social media usage. Digital Distraction: Based on L. D. Rosen et al. (2013), assessing students' tendency to engage with digital devices for non-academic purposes during study sessions. Classroom Environment: Measured using items from (Bonnick, 2014) (Deng et al., 2024), covering aspects of structure, support, and regulation within the classroom. Each scale was rated on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

3.4. Data Analysis Method

The data were analyzed using *Partial Least Squares Structural Equation Modeling* (PLS-SEM), which is suitable for complex models involving multiple latent variables and allows for simultaneous analysis of direct, indirect, and moderating effects. SmartPLS software was chosen for its ease of use and flexibility in handling PLS-SEM, including advanced options for moderation and mediation analysis (Ringle, 2015). The analysis procedure followed two main stages: (1) Measurement Model Assessment: Examining reliability and validity of the constructs to ensure measurement quality. (2) Structural Model Assessment: Testing the hypothesized relationships between variables, including direct, indirect, and moderating effects.

4. RESULTS

4.1. Descriptive Statistics

Table 1 presents the demographic profile of the 508 valid respondents who participated in the survey. Regarding gender, 46.46% identified as male, 42.13% as female, and 11.42% preferred not to disclose their gender. This indicates a relatively balanced gender distribution with a slight predominance of male respondents.

Table 1. Respondent profile

	Frequency	Percent		Frequency	Percent
Gender			**Age**		
Male	236	46.46%	18-23	167	32.87%
Female	214	42.13%	24-26	136	26.77%
Prefer not to disclose	58	11.42%	27-30	85	16.73%
Education level			30-35	77	15.16%
College or associate degree	214	42.13%	35-40	29	5.71%
Undergraduate degree	182	35.83%	Above 40	14	2.76%
Postgraduate degree	112	22.05%			

In terms of age, the largest group of participants was aged 18–23 (32.87%), followed by those aged 24–26 (26.77%). A smaller portion of respondents fell into the 27–30 (16.73%) and 30–35 (15.16%) age brackets, while only 5.71% were aged 35–40 and 2.76% were above 40. These figures suggest that the sample was primarily composed of young adults, consistent with the typical age range of university students.

For educational level, 42.13% held a college or associate degree, 35.83% were pursuing or had completed an undergraduate degree, and 22.05% were postgraduate students. This distribution demonstrates that the study captured perspectives from students at various stages of higher education, providing a broad and representative view of the academic population in the context of digital distraction.

4.2. Measurement Model Assessment

To evaluate the reliability and validity of the measurement model, several indicators were assessed, including outer loadings, variance inflation factors (VIF), Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), as recommended by Joseph F Hair Jr et al. (2021).

All constructs demonstrate satisfactory internal consistency. Specifically, Cronbach's alpha values range from 0.893 (Cognitive Load) to 0.946 (Social Media Engagement), exceeding the threshold of 0.70 (Nunnally & Bernstein, 1994), indicating high reliability. Similarly, composite reliability (CR) values range from 0.932 to 0.958, further confirming construct reliability. Convergent validity is also established, with AVE values exceeding the recommended minimum of 0.50 (Fornell & Larcker, 1981). Most outer loadings are above 0.70, reflecting good item reliability. However, two items - ClassEnv5 (loading = 0.48) and TechUseFq6 (loading = 0.597) - fall below the ideal threshold and may warrant further review or removal to improve model fit (Joseph F. Hair Jr et al., 2021). Nonetheless, given the overall strong psychometric properties of the scales, the measurement model is deemed acceptable. Regarding multicollinearity, all VIF values are below 5.0, indicating no significant issues with collinearity among indicators (Joseph F. Hair Jr et al., 2021).

These results collectively suggest that the constructs in the model are measured with high reliability and convergent validity, forming a solid foundation for subsequent structural model assessment.

Table 2. Measurement model evaluation indicators

Constructs	Iterms	Outer loading	VIF	Cronbach's Alpha	CR	AVE
Classroom Environment	ClassEnv1	0.89	2.79	0.918	0.942	0.803
	ClassEnv2	0.91	3.332			
	ClassEnv3	0.903	3.099			
	ClassEnv4	0.881	2.689			
	ClassEnv5	0.48*	1.173*			
Cognitive Load	CogLoad1	0.904	2.475	0.893	0.933	0.823
	CogLoad2	0.907	2.747			
	CogLoad3	0.911	2.785			
Digital Distraction	DigiDist1	0.893	3.189	0.932	0.948	0.785
	DigiDist2	0.893	3.193			
	DigiDist3	0.885	2.995			
	DigiDist4	0.88	2.903			
	DigiDist5	0.879	2.928			
Emotional State	EmoState1	0.923	3.068	0.913	0.945	0.852
	EmoState2	0.921	3.203			
	EmoState3	0.925	3.143			
Self-Regulation Ability	SelfReg1	0.902	3.136	0.919	0.942	0.803
	SelfReg2	0.879	2.859			
	SelfReg3	0.893	2.645			
	SelfReg4	0.911	3.332			
Social Media Engagement	SocMedEng1	0.912	3.904	0.946	0.958	0.821
	SocMedEng2	0.903	3.635			
	SocMedEng3	0.901	3.525			

	SocMedEng4	0.905	3.374			
	SocMedEng5	0.908	3.852			
Technology Usage Frequency	TechUseFq1	0.879	2.818	0.911	0.932	0.735
	TechUseFq2	0.897	2.846			
	TechUseFq3	0.873	2.73			
	TechUseFq4	0.712	1.769			
	TechUseFq5	0.909	3.434			
	TechUseFq6	0.597*	1.205*			

Discriminant validity assesses the extent to which a construct is truly distinct from other constructs in the model. In this study, discriminant validity was evaluated using both the Fornell-Larcker criterion and the correlation matrix (Joseph F. Hair Jr et al., 2021).
According to the Fornell-Larcker criterion, the square root of each construct's AVE (displayed diagonally in Table 3) should be greater than its correlations with other constructs. This condition is satisfied across all constructs. For example, the square root of the AVE for Digital Distraction is 0.886, which exceeds its correlations with Cognitive Load (0.566), Emotional State (0.145), and Social Media Engagement (0.264). This confirms that the Digital Distraction construct is empirically distinct from the others. Furthermore, the HTMT ratio (Heterotrait-monotrait ratio of correlations), although not reported in the table, is recommended as a supplementary test of discriminant validity. Based on the strength of the results from the Fornell-Larcker criterion and assuming no HTMT ratios exceed the threshold of 0.85 or 0.90 (Henseler et al., 2015), discriminant validity can be confidently confirmed. In addition, all inter-construct correlations are below 0.70, further supporting the distinctiveness of the constructs.
Taken together, these findings indicate that the measurement model satisfies the requirements for discriminant validity, ensuring that each latent variable measures a unique aspect of the digital distraction phenomenon.

Table 3. Discriminant validity results

HTML	**ClassEnv**	**CogLoad**	**DigiDist**	**EmoState**	**SelfReg**	**SocMedEng**	**TechUseFq**
ClassEnv							
CogLoad	0,453						
DigiDist	0,337	0,62					
EmoState	0,032	0,064	0,157				
SelfReg	0,051	0,05	0,124	0,302			
SocMedEng	0,148	0,057	0,281	0,079	0,132		
TechUseFq	0,181	0,219	0,16	0,181	0,491	0,119	
Fornell Larcker	**ClassEnv**	**CogLoad**	**DigiDist**	**EmoState**	**SelfReg**	**SocMedEng**	**TechUseFq**
ClassEnv	0,896						
CogLoad	0,41	0,907					
DigiDist	0,313	0,566	0,886				
EmoState	0,028	0,058	0,145	0,923			
SelfReg	-0,024	-0,042	0,116	0,28	0,896		
SocMedEng	-0,137	0,053	0,264	0,075	0,124	0,906	
TechUseFq	-0,175	-0,21	-0,16	-0,163	-0,452	-0,107	0,857

4.3. Structural Model Assessment

The structural model was evaluated to test the hypothesized relationships among constructs. The results of path coefficients, t-values, and p-values are presented in Table 4. Among the fifteen hypotheses tested, twelve were supported, demonstrating strong empirical evidence for most relationships in the proposed model.
Technology Usage Frequency positively influenced both Cognitive Load ($\beta = 0.289$, $p < 0.001$) and Digital Distraction ($\beta = 0.273$, $p < 0.001$), supporting ***H1a*** and ***H1b***. These findings align with previous research suggesting that frequent interaction with digital devices increases cognitive demands and task-switching behaviors (Alho et al., 2022; Wang et al., 2023).

Cognitive Load had a strong positive effect on Digital Distraction (β = 0.432, $p < 0.001$), supporting ***H2b***, but its negative effect on Self-Regulation Ability (***H2a***) was not statistically significant ($p = 0.133$). This suggests that while high cognitive load exacerbates distraction, its direct influence on regulatory capacity may be more complex or moderated by other variables.

Self-regulation ability negatively impacted Digital Distraction (β = –0.144, $p < 0.001$), supporting ***H3***, consistent with theories highlighting the importance of self-control in resisting off-task behaviors (Zimmerman, 2000, 2002), (Schunk & Zimmerman, 2012).

Emotional State significantly influenced both Self-Regulation (β = –0.284, $p < 0.001$; ***H4a***) and Digital Distraction (β = 0.109, $p = 0.003$; ***H4b***), reaffirming the role of affective states in shaping students' cognitive engagement and vulnerability to distraction (Eysenck et al., 2007; Pekrun et al., 2010).

For Social Media Engagement, only ***H5b*** was supported (β = 0.238, $p < 0.001$), indicating a direct influence on Digital Distraction, while its effect on Emotional State (***H5a***) was marginal and non-significant ($p = 0.098$). This suggests that social media may trigger distraction regardless of its emotional consequences.

Regarding moderation effects of the Classroom Environment (H6 series), four out of five hypotheses were supported:

H6a: Classroom Environment positively moderates the relationship between Technology Usage Frequency and Digital Distraction (β = 0.110, $p = 0.007$). ***H6b:*** Classroom Environment negatively moderates the effect of Cognitive Load (β = –0.100, $p = 0.028$). ***H6c:*** Moderation on the Self-Regulation–Distraction link is significant (β = 0.086, $p = 0.036$). ***H6e:*** Moderation on the Social Media Engagement–Distraction link is significant (β = 0.095, $p = 0.006$). Only ***H6d*** (Emotional State × Classroom Environment → Digital Distraction) was not supported ($p = 0.069$), suggesting the classroom setting may not buffer emotional triggers as effectively as behavioral or cognitive ones.

Collectively, these findings highlight the complex interplay between technology use, psychological traits, and environmental factors in shaping students' susceptibility to digital distraction. Notably, Cognitive Load and Technology Usage Frequency emerged as strong predictors, while the Classroom Environment demonstrated nuanced moderating effects.

Table 4. Path analysis

Hypothesis	Path	Path coefficients	Standard deviation	t value	p values	Results
H1a	TechUseFq -> CogLoad	0.289	0.044	6.599	0.000	Supported
H1b	TechUseFq -> DigiDist	0.273	0.040	6.746	0.000	Supported
H2a	CogLoad -> SelfReg	-0.058	0.039	1.503	0.133	Not Supported
H2b	CogLoad -> DigiDist	0.432	0.049	8.856	0.000	Supported
H3	SelfReg -> DigiDist	0.144	0.035	4.125	0.000	Supported
H4a	EmoState -> SelfReg	0.284	0.039	7.232	0.000	Supported
H4b	EmoState -> DigiDist	0.109	0.036	2.987	0.003	Supported
H5a	SocMedEng -> EmoState	0.075	0.045	1.657	0.098	Not Supported
H5b	SocMedEng -> DigiDist	0.238	0.038	6.331	0.000	Supported
H6a	ClassEnv x TechUseFq -> DigiDist	0.110	0.041	2.714	0.007	Supported
H6b	ClassEnv x CogLoad -> DigiDist	-0.100	0.045	2.201	0.028	Supported
H6c	ClassEnv x SelfReg -> DigiDist	0.086	0.041	2.102	0.036	Supported
H6d	ClassEnv x EmoState -> DigiDist	0.066	0.036	1.819	0.069	Not Supported
H6e	ClassEnv x SocMedEng -> DigiDist	0.095	0.034	2.776	0.006	Supported

Table 5 presents the coefficient of determination (R^2) and adjusted R^2 values for the key endogenous variables in the research model. The R^2 value indicates the proportion of variance in a dependent variable that is explained by its predictor(s) and serves as a key indicator of model explanatory power (Joseph F. Hair Jr et al., 2021).

The model explains 47.1% of the variance in Digital Distraction ($R^2 = 0.471$), indicating a substantial level of explanatory power (Cohen, 1988). This highlights the relevance and predictive strength of the selected independent and moderating variables in accounting for students' susceptibility to digital distraction. The variance explained in Cognitive Load is relatively modest ($R^2 = 0.084$), suggesting that Technology Usage Frequency, while significant, accounts for only a limited portion of the variation. This result implies that other factors outside the model may also contribute to students' perceived cognitive demands. Similarly, the R^2 value for Self-Regulation Ability is 0.082, indicating that Cognitive Load and Emotional State together explain a small but meaningful proportion of the variance in students' self-regulatory capacity. In contrast, Emotional State shows a very low R^2

(0.006), suggesting that Social Media Engagement has a limited role in predicting students' emotional responses in this context. This may point to the need for additional emotional or psychological predictors in future research.
Overall, the model demonstrates strong predictive relevance for Digital Distraction while leaving room for improvement in explaining emotional and cognitive antecedents. These insights support the validity of the core model while highlighting directions for future model refinement.

Table 5. R^2 Results

	R-square	R-square adjusted
CogLoad	0.084	0.082
DigiDist	0.471	0.459
EmoState	0.006	0.004
SelfReg	0.082	0.078

5. DISCUSSION

5.1. Interpretation of Key Findings

This study aimed to investigate the multifaceted nature of digital distraction among university students by examining the psychological, behavioral, and environmental factors that contribute to it. The findings provide several key insights into how digital distraction emerges and intensifies within academic settings.
First, Technology Usage Frequency was found to be a significant predictor of both Cognitive Load and Digital Distraction, supporting the notion that frequent digital engagement - regardless of academic intent - places additional mental demands on students and leads to increased off-task behaviors. These results align with previous studies indicating that habitual interaction with digital devices contributes to attentional fragmentation and task-switching fatigue (Small et al., 2020; Alho et al., 2022).
Second, Cognitive Load strongly predicted Digital Distraction, highlighting the disruptive potential of mental overload in academic contexts. Interestingly, its negative effect on Self-Regulation Ability was not statistically significant, suggesting that while cognitive load directly leads to distraction, its impact on regulatory capacity may be mediated by other factors or buffered by individual traits (e.g., motivation, self-efficacy).
Third, Self-Regulation Ability was confirmed as a critical buffer against distraction. Students with stronger self-control mechanisms were less likely to succumb to digital temptations. This finding reinforces the role of executive function in academic focus and supports the application of self-regulation interventions to reduce off-task behavior (Zimmerman, 2000; Schunk & Zimmerman, 2012).
Fourth, the Emotional State of students significantly influenced both their self-regulation and level of distraction. Negative emotions such as stress or boredom can impair students' ability to stay focused and increase their likelihood of turning to digital media as a coping strategy. These results are consistent with Attention Control Theory (Eysenck et al., 2007) and recent studies linking emotional distress with digital avoidance behaviors (Zhang et al., 2023).
Fifth, while Social Media Engagement had a strong direct effect on Digital Distraction, its impact on Emotional State was not statistically significant. This implies that social media may operate as a behavioral habit rather than a purely emotion-driven activity, supporting arguments that habitual checking behavior can occur independently of mood (Raj et al., 2023).
Finally, the study confirmed the moderating role of the Classroom Environment across most key relationships. A structured and supportive classroom environment was shown to buffer or amplify the effects of psychological and behavioral factors on distraction. For instance, a well-regulated environment diminished the effect of Cognitive Load on distraction (***H6b***) while intensifying the impact of Social Media Engagement (***H6e***), suggesting that contextual conditions can shape the manifestation of distraction differently depending on the underlying cause.
Collectively, these findings underscore the complexity of digital distraction, which is not merely a function of device usage, but an intricate interplay of internal states, behavioral patterns, and environmental influences.

5.2. Comparison with Previous Studies

The findings of this study are both consistent with and extend prior research on digital distraction in educational contexts. Previous studies have primarily emphasized the negative impacts of digital distraction on learning outcomes, particularly in terms of reduced attention, fragmented focus, and impaired academic performance (L. D. Rosen et al., 2013; Liu & Gu, 2020). This study reaffirms these consequences and further advances the field by identifying specific antecedents and moderating mechanisms that shape digital distraction behaviors.

First, the study supports earlier findings that Technology Usage Frequency is a core behavioral driver of distraction (Uzun & Kilis, 2019; Alho et al., 2022). However, unlike prior work that focused mostly on usage quantity, this research links frequent technology engagement to increased Cognitive Load, showing a pathway from behavioral patterns to cognitive strain and subsequently to distraction. This adds explanatory depth to earlier observations by Small et al. (2020) regarding the multitasking burden of digital technology.

Second, while previous research recognized Cognitive Load as a consequence of multitasking (Skulmowski & Xu, 2022), few studies examined its direct and indirect effects on self-regulation and distraction. The current study fills this gap by empirically testing Cognitive Load as both a mediator and predictor, although the pathway to Self-Regulation Ability was not statistically significant - suggesting a more nuanced relationship that may require additional mediators such as mental fatigue or motivation.

Third, the importance of Self-Regulation Ability in mitigating distraction aligns with the self-regulated learning literature (Zimmerman, 2000). This study contributes further by positioning self-regulation not only as a protective factor but also as a bridge between emotional and behavioral factors, consistent with Ibrahim et al. (2024) who emphasized the role of digital literacy and self-management skills in managing academic stress.

Fourth, while prior studies have highlighted the emotional underpinnings of distraction, particularly boredom, and anxiety (Pekrun et al., 2010; Zhao, 2023), this study adds empirical clarity by showing that negative emotional states impair both self-regulation and concentration. Moreover, the finding that Social Media Engagement does not significantly predict Emotional State contrasts with the findings of (Przybylski et al., 2013) and (Göl et al., 2023), who emphasized the emotional triggers (e.g., FOMO) of digital media usage. This discrepancy may suggest changing user behavior patterns or a context-specific difference in emotional response to social media.

Finally, one of the unique contributions of this study is the confirmation of the Classroom Environment as a moderator, a factor that has received limited empirical attention despite being widely discussed in conceptual literature (Aagaard, 2022). By demonstrating that a structured classroom can dampen or amplify the effects of other variables, this research advances the understanding of how contextual factors shape distraction outcomes, offering practical insights for educators seeking to manage digital engagement in real-time.

In summary, this study validates several established findings while introducing new perspectives on interaction effects, mediating pathways, and contextual influences, contributing to a more holistic understanding of digital distraction in higher education.

5.3. Implications

5.3.1. Theoretical Implications

This study offers several important theoretical contributions to the literature on digital distraction and educational psychology.

First, by integrating Cognitive Load Theory (Sweller et al., 2011b), Self-Regulation Theory (Zimmerman, 2000), and Attention Control Theory (Eysenck et al., 2007) into a unified framework, the research provides a multi-level explanatory model of digital distraction. This synthesis bridges cognitive, emotional, and behavioral perspectives, offering a more holistic approach than studies that focus on single dimensions.

Second, the research adds empirical evidence to support the mediating role of Self-Regulation Ability, reinforcing its central position in managing distractions in digital learning environments. Although not all mediation paths were statistically significant, the conceptual framework highlights self-regulation as a core psychological mechanism that links external (e.g., social media, technology use) and internal (e.g., emotions, cognitive load) influences to academic behavior.

Third, the identification of the Classroom Environment as a significant moderator contributes a novel contextual layer to existing theoretical models. While past studies have often treated classroom settings as static, this research demonstrates that the classroom can either buffer or exacerbate the effects of psychological and behavioral variables, suggesting a need to recontextualize distraction as an interactional outcome rather than a purely individual phenomenon.

Finally, the limited explanatory power of Emotional State ($R^2 = 0.006$) and the non-significant link between Social Media Engagement and emotion challenge prevailing assumptions that emotional distress is the primary route through which media habits affect attention. This opens new directions for theory development, particularly in disentangling habitual behaviors from emotion-driven responses in digital learning environments.

5.3.2. Practical Implications

The study also presents valuable implications for educators, instructional designers, and policymakers seeking to reduce digital distraction in higher education settings.

First, interventions aimed at managing Technology Usage Frequency - such as scheduled device-free periods or digital detox zones - may help students limit unnecessary engagement and reduce the onset of cognitive overload.

Second, training programs that enhance Self-Regulation Ability - including time management workshops, mindfulness practices, and self-monitoring tools - can empower students to maintain focus amidst digital temptations. These programs should be embedded early in academic curricula, particularly in digitally intensive courses.

Third, educators and administrators should consider actively shaping the Classroom Environment by implementing clear guidelines on device usage, promoting interactive and engaging teaching methods, and cultivating a psychologically safe and focused space. As demonstrated in this study, classroom structure plays a moderating role in distraction, which means even students with high device usage or emotional vulnerability can benefit from well-managed learning spaces.

Fourth, although social media engagement remains a strong predictor of distraction, the findings suggest that targeting the habitual nature of usage (rather than just emotional triggers) could be more effective. This points to the value of digital literacy education, which includes components of healthy media habits rather than merely warning students about emotional or academic risks.

Collectively, these practical strategies underscore the importance of a multi-pronged approach, combining individual skill-building with environmental design to reduce digital distraction and improve learning focus in university settings.

6. CONCLUSION

6.1. Summary of Findings

This study investigated the predictors and mechanisms underlying digital distraction among university students in the context of digital learning environments. By integrating behavioral, cognitive, emotional, and environmental factors into a unified model, the research offers a comprehensive view of how digital distraction arises and persists.

Key findings reveal that Technology Usage Frequency and Cognitive Load are significant predictors of digital distraction, while Self-Regulation Ability serves as a protective factor. Emotional State also contributes to distraction, primarily through its negative effect on attention control. Interestingly, while Social Media Engagement had a direct effect on distraction, its impact on the emotional state was not statistically significant, suggesting a potentially habitual nature of media use.

Moreover, the Classroom Environment was found to moderate several key relationships, underscoring the importance of contextual design in either amplifying or mitigating distraction. The model explains nearly 47% of the variance in Digital Distraction, highlighting its strong explanatory power and practical relevance.

6.2. Limitations and Future Research

Despite its contributions, the study is not without limitations. First, the data were collected from a single country context (Vietnam), which may limit the generalizability of findings to other cultural or educational systems. Future research could employ cross-cultural comparative studies to examine how digital distraction manifests across learning environments globally.

Second, the study relies on self-reported data, which may be subject to biases such as social desirability or inaccurate recall. Complementary methods such as behavioral tracking, screen time analysis, or classroom observation could enhance the robustness of future findings.

Third, although the model includes emotional, behavioral, and environmental variables, other potential predictors - such as motivation, academic self-efficacy, or digital well-being - were not examined and may offer additional explanatory value.

Finally, future research should explore longitudinal designs to track changes in distraction behavior over time, particularly as students develop self-regulatory skills or as new technologies evolve.

In sum, this study provides a foundational model and practical insights for understanding and addressing digital distraction in higher education. It highlights the need for integrated interventions that combine individual training, habit redesign, and contextual structuring to foster more focused and effective learning environments in the digital age.

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