Digital Distractions: An Analysis of Phone Usage Patterns, Cultural Influences, and Academic Performance Among University Students

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Abstract

This study delves into the dynamics of phone usage patterns, cultural influences, and academic performance among university students across Taiwan and Vietnam, examining 387 students via an online survey. Contrary to the predictions of cognitive load theory, the findings reveal that the mere proximity of phones during study sessions does not directly impact academic performance. Instead, the study identifies several moderating factors that shape this relationship. Notably, the quality of the university, the field of study, and specific cultural orientations—particularly long-term orientation and indulgence—significantly influence how phone location affects performance. Students from higher-ranked universities and those with a strong long-term focus exhibited greater resilience to potential distractions posed by nearby phones, while indulgent tendencies tended to amplify the negative impacts. These findings underscore the pivotal role of cultural context in effectively addressing digital distractions within educational settings. Advocating for a culturally responsive approach, the study suggests that interventions and policies should be specifically tailored to the distinct cultural, institutional, and individual factors that influence students' interactions with technology and its effects on learning. By embracing this multifaceted understanding, educators and policymakers can develop more effective strategies to enhance student focus and academic success in the digital era.

Keywords: Digital Distraction, Academic Performance, Cultural Influences, Mobile Phone Usage, Study Habits

1. Introduction

1.1. Context and Importance of Studying Digital Distraction

The widespread adoption of digital technologies like smartphones and laptops has profoundly impacted learning environments. These devices grant students convenient access to information, enable mobile learning, and facilitate collaboration (Anshari et al., 2017). However, they also pose significant distraction risks. Studies consistently show that digital distractions negatively affect educational outcomes. College students report technology causing decreased attention, hindered studying, and reduced learning during class (Flanigan and Babchuk, 2015; Kuznekoff and Titsworth, 2013). One survey found that 80% of undergraduates say digital distractions impair their performance (McCoy, 2016).

Detrimental impacts also emerge outside class. Media multitasking while studying reduces reading comprehension and academic performance (Wu, 2017). Having phones nearby, even if unused, reduces available cognitive capacity (Ward et al., 2017a). Such distracted learning partially explains the growing lack of deep focus among students (Richtel, 2010).

Given the centrality of mobile technologies in students' lives, understanding digital distraction is crucial. Factors like phone location patterns while studying and cultural influences must be examined. Cross-cultural research can illuminate whether distracted behaviours are universal or shaped by cultural norms. Comparing contexts like the U.S., China, and Africa could provide insights into how indulgence versus restraint or individualism versus collectivism affect distractions. Economic and technological variations between these regions likely also play a role (Chau et al., 2002).

Investigating links between distraction and academic performance provides pragmatic insights. If distracted learning hinders outcomes, policies limiting access during class or study periods may be warranted. Alternatively, training students in effective technology regulation skills could prove beneficial. Overall, research on digital distractions enables the development of learning environments compatible with mobile technologies while mitigating their risks. This study aims to provide such insights by analyzing phone location patterns, cultural influences, and impacts on performance among university students across divergent global contexts.

1.2. Aim of the Research with a Focus on Cultural Influences

This study aims to analyze digital distractions, specifically phone usage patterns, and their impacts on academic performance among university students across divergent cultural contexts. Prior research indicates that cultural values shape technology adoption and use behaviours (Srite and Karahanna, 2006; Straub et al., 1997). For instance, individualism versus collectivism and indulgence versus restraint orientation influence motivations for and responses to technology (Downing et al., 2003; Jarvenpaa and Leidner, 1998). Cross-cultural variations in concepts of time, communication norms, and gender roles also affect technology engagement (Chau et al., 2002; Hill et al., 1998). Comparing phone usage patterns between students from contrasting cultures, such as the U.S., China, and African nations, can provide insights into how cultural tendencies shape technology distractions. Investigating links between these distraction behaviours and academic achievement will also illuminate cultural differences in the impacts of digital interference. This cross-cultural analysis will further understand how cultural orientations and values manifest in technology usage behaviours and their implications in educational contexts.

Specifically, this study will examine university students in the U.S., China, and select African countries. These regions represent divergent cultural dimensions based on Hofstede's cultural values framework (Hofstede, 2001a). The U.S. reflects higher individualism and indulgence compared to China and African nations' more collectivist and restrained orientations. China also demonstrates greater pragmatism than the U.S. and Africa. Differences in economic development, infrastructure, and technology penetration between these countries may also contribute to variations in distraction patterns (Chau et al., 2002; Watson et al., 1997; Forum et al., 2012).

The study will survey students within these contexts to capture phone location patterns, such as face-up near them or in another room, while studying. It will also measure cultural values like individualism-collectivism and indulgence-restraint. Academic performance data will be gathered to assess relationships between phone usage, cultural tendencies, and grades or GPA. Comparing results between regions will highlight how cultural dimensions align with distraction behaviours and achievement impacts.

Findings can inform policies and interventions to maximise the benefits of mobile technologies for learning while mitigating detrimental behaviours. If associations between cultural values and distracted usage emerge, technology regulation initiatives could be tailored based on prevailing cultural norms. The study also has theoretical implications regarding the applicability of established technology adoption models across diverse cultures. Overall, these insights will enable the development of digitally integrated but distraction-limited learning environments suited to the values and needs of unique cultural settings.

1.3. Research Question or Hypothesis

This study proposes several hypotheses regarding the relationships between students' phone usage patterns, cultural backgrounds, academic disciplines, and educational outcomes. Specifically, it is predicted that the closer a student's phone is in proximity during study sessions, the lower their academic performance will be, reflecting increased digital distraction. Additionally, the correlation between phone location and grades is expected to differ significantly across students from various national cultures, suggesting cultural variances in technology distraction impacts. Nationality is also hypothesized to influence grades directly, indicating potential cultural differences in achievement. Furthermore, the association between proximity and performance is hypothesized to depend on students' course of study, with specific disciplines exacerbating technology interference more than others. Testing these hypotheses will provide insights into how cultural values, academic contexts, and mobile technology habits intersect to shape educational experiences and outcomes among university students. The study aims to empirically assess these relationships to inform policies that effectively integrate devices into diverse learning environments.

1.4. Structure of the Paper

The structure of this paper is organized as follows: Section 2 reviews pertinent literature, setting the contextual backdrop. Section 3 elaborates on the research methodology, laying the groundwork for empirical analysis and formulating guiding research questions. Section 4 unveils the study's findings, prefacing comprehensive discussion and analytical exploration in Section 5. The conclusion in Section 6 encapsulates critical insights, articulates limitations, and suggests avenues for future inquiry, thereby bridging theoretical and empirical dimensions

2. Literature Review

2.1. Impact of Digital Distraction on Academic Performance

In the era of digital advancements, the omnipresence of digital tools has significantly altered the landscape of human interaction and productivity. One of the most pressing issues arising from this digital immersion is the phenomenon of digital distraction. This pervasive force undermines performance across various domains of life, including academic achievement, workplace productivity, and personal goal attainment (Carr, 2010; Gazzaley and Rosen, 2016). Digital distraction, characterized by the constant pull of notifications, emails, and the endless allure of the internet, poses a formidable challenge to maintaining focus and achieving high performance levels. This phenomenon is not limited to any single source of distraction but is emblematic of the broader digital ecosystem that includes smartphones, computers, tablets, and other digital devices (Ward et al., 2017b; Kushlev et al., 2016).

The impact of digital distraction on academic performance is well-documented. Several studies have shown a strong association between increased digital distraction and diminished academic outcomes. For students, the constant interruption from digital notifications can disrupt cognitive processes critical for learning, memory consolidation, and attention regulation, leading to decreased academic performance (Lepp et al., 2015a; Stothart et al., 2015; **?**; **?**). This effect is particularly pronounced in tasks with higher executive function demands, such as mathematics, where complex cognition and focused attention are essential (Sirin, 2005).

Empirical studies have consistently reported that digital distractions, such as texting, browsing the internet, and using social media during class, are prevalent among college students, with some estimates suggesting that students engage in off-task digital activities for 40-60% of class time (Kraushaar and Novak, 2010; Kornhauser et al., 2016; Hendrick, 2018). This off-task behaviour has been linked to poorer note-taking, lower quiz and exam scores, decreased course grades, and lower overall GPAs (Waite et al., 2018b). Moreover, digital distractions can have a ripple effect, as students seated near peers engaged in off-task digital activities may also experience hindered learning and academic achievement (Aagaard, 2015).

Addressing digital distraction requires a multifaceted approach that includes individual strategies, technological solutions, and organizational policies. Individuals can adopt practices such as designated tech-free times, mindfulness meditation (Kabat-Zinn, 1994), and the use of productivity apps designed to minimize distractions. Technological solutions, such as website blockers and notification management tools, can also play a critical role in mitigating digital distractions. Furthermore, organizations and educational institutions can implement policies that promote focused work periods and provide training on digital literacy and time management. By addressing digital distraction from multiple angles, students can cultivate a more conducive learning environment and maximize their academic potential.

2.2. Mobile Phone Usage and Student Outcomes

The exploration into the impact of mobile phone usage on student outcomes has unfolded a complex narrative that underscores both the potential benefits and the challenges posed by these devices within educational settings. Extensive research into this area has illuminated the dual nature of mobile phones, which, on the one hand, serve as pivotal educational tools, enhancing access to learning materials and facilitating innovative learning and teaching methodologies.

On the other hand, they emerge as sources of distraction, potentially undermining academic performance and student well-being.

The utilization of mobile phones in educational contexts has been shown to significantly augment the learning experience, providing students with unprecedented access to digital textbooks, academic applications, and online courses. This access enables a more flexible and dynamic educational environment, accommodating a variety of learning preferences and styles. The pedagogical integration of mobile technology has been associated with notable improvements in student engagement, motivation, and outcomes across different academic disciplines (Thomas and Muñoz, 2016; Kuznekoff and Titsworth, 2013; Justin et al., 2022). This positive impact is attributed to the interactive nature of mobile learning, which encourages active participation and facilitates a more personalized learning journey.

Conversely, the widespread adoption of mobile phones among students has prompted concerns regarding their potential to distract and detract from the educational experience. The lure of non-academic mobile phone use, including texting, social media, and gaming, especially during instructional time, poses a significant challenge to maintaining student focus and engagement with academic material. Such distractions have been empirically linked to diminished academic achievements (Lepp et al., 2015b; Rosen et al., 2011). Additionally, the overuse of mobile phones has been associated with sleep disturbances, contributing to a decline in cognitive functions crucial for learning and memory retention, further impacting academic performance negatively (Demirci et al., 2015).

The influence of mobile phone usage on academic outcomes is not uniform but varies with factors, including the students' age, their field of study, and the strategies employed to integrate mobile technology into the learning process. It appears that the impact of mobile phones is more pronounced and potentially disruptive among younger students compared to their older counterparts, who might leverage mobile technology more effectively for educational purposes through self-regulation (Selwyn, 2013; Wentworth and Middleton, 2013).

Educational institutions have grappled with these challenges, adopting a range of policies from complete prohibitions of mobile phones to their strategic incorporation into classroom activities, guided by structured pedagogical principles. The success of these policies is intricately linked to the educational context and objectives, highlighting the importance of aligning mobile phone use with educational goals to harness their potential benefits while mitigating associated risks.

The dynamic interplay between mobile phone usage and student outcomes underscores a critical balance within the educational sphere. Mobile devices, characterized by their dual capacity to facilitate and impede learning, present educators and learners with the challenge of leveraging technology to enhance educational experiences while concurrently safeguarding against potential distractions. This equilibrium is crucial as educational practices continue to integrate with evolving mobile technologies, necessitating further exploration into practical strategies that optimize the benefits of mobile phones in academic contexts. As the discourse progresses, attention must also be given to the cultural dimensions of technology use in education, a consideration that introduces an additional layer of complexity to understanding and navigating the impact of digital distractions on student performance.

2.3. Cultural Dimensions as Moderators

Cultural factors can significantly influence various aspects of human behaviour (Martens and Pham, 2021), including academic performance and the use of technology. Geert Hofstede's cultural dimensions theory provides a useful framework for understanding the impact of cultural values on individual and organizational practices (De Mooij and Hofstede, 2010; Hofstede, 2001b). Hofstede identified six primary cultural dimensions: Power Distance, Individualism/Collectivism, Motivation[1], Uncertainty Avoidance, Long-Term Orientation, and Indulgence/Restraint.

While all of Hofstede's dimensions can potentially influence educational experiences and outcomes, this study will primarily focus on the Long-Term Orientation, Motivation (Achievement vs Nurturing Orientation), and Indulgence/Restraint dimensions due to their relevance in understanding student behaviours related to digital distractions and academic performance. Long-term orientation has been associated with students' academic motivation, study habits, overall performance, and use of technology and susceptibility to distractions (Hofstede, 2001b; Wilmer et al., 2017; Kim et al., 2019). The Motivation dimension can influence the strategies students employ to manage distractions, with achievement-oriented cultures fostering a focus on success that may lead to proactive measures against distractions (Hofstede, 2001b). Additionally, the Indulgence/Restraint dimension has been linked to students' attitudes towards distracting behaviours, with indulgent cultures potentially exhibiting higher levels of distraction and lower self-regulation (Hofstede, 2011; Pishghadam et al., 2020).

[1]Hofstede's "Masculinity vs. Femininity" dimension was renamed to "Motivation towards Achievement and Success" to address customer discomfort with the binary gender framing while retaining the original dimension's definition and country scores (Hofstede Insights)

2.3.1. *Indulgence vs. Restraint*

The indulgence dimension reflects the degree to which a society allows relatively free gratification of basic and natural human desires related to enjoying life and having fun (Hofstede, 2011). Cultures high in indulgence tend to have a more relaxed approach to personal life, while restraint cultures have stricter social norms that control the gratification of needs (Hofstede, 2011). In the context of this study, which investigates the impact of digital distractions on academic performance, the indulgence dimension may play a significant role as a moderator.

Indulgent cultures may be more prone to digital distractions and cyberslacking behaviours during class, as students feel less restricted in satisfying their desires (Hanif and Imran, 2022; Koay and Poon, 2022). The social norms and pressures to conform are less stringent, allowing students to indulge in non-academic activities more freely (Ugrin et al., 2018; Szopiński and Bachnik, 2022). Conversely, restrained cultures may exhibit more robust self-regulation and adherence to academic norms, as societal values emphasize self-control and duty over immediate gratification (Henadirage and Gunarathne, 2023).

Additionally, the indulgence dimension underscores the variance in how indulgent versus restrained cultures navigate the temptations of immediate pleasure, such as phone use during study time. Indulgent cultures may display a greater tolerance for the presence and use of phones, viewing them as integral to enjoying life and study breaks. In contrast, restrained cultures might prioritize academic focus, advocating for stricter self-discipline regarding phone usage (Dangelico et al., 2020). By integrating these cultural dimensions, our analysis sheds light on the intricate relationship between cultural norms and individual behaviour outside the traditional classroom setting, offering insights into how cultural backgrounds shape students' approaches to managing potential technological distractions. This nuanced understanding aids in recognizing the diverse cultural determinants that impact students' study habits and their interaction with mobile phones, facilitating the development of more effective strategies for maintaining academic focus amidst the proliferation of digital distractions.

2.3.2. *Motivation*

Motivation plays a fundamental role in influencing student academic performance, which is significantly shaped by students' beliefs about their capabilities and the outcomes of their academic endeavours (Abdelrahman, 2020). These beliefs, encompassing both outcome expectations and perceptions of personal competence, are essential in determining how much value students attach to their educational tasks and their expectations for success (Wigfield and Eccles, 2020). Higher motivation levels typically lead to greater effort and higher achievement, as students who believe they can successfully complete tasks and find value in them are more likely to excel (Wolters and Brady, 2021). This correlation is consistently supported across various educational research studies, showing a direct link between motivation levels and academic performance (Andini and Rusmini, 2022; Diaconu-Gherasim et al., 2022).

However, the relationship between motivation and academic performance is complex and is influenced by cultural factors that vary significantly across different regions and educational systems (Behr et al., 2020; Vuong et al., 2021; Martens and Bui, 2023). While studies in Western contexts like the United States have shown a negative correlation between extrinsic motivation and academic achievement, this trend does not uniformly apply in more collectivist cultures such as those in Taiwan and Hong Kong, where extrinsic motivation might not detrimentally impact academic success (Hennebry-Leung and Gao, 2021). These cultural variations highlight the need to consider cultural norms and values when assessing the impact of motivation on academic outcomes, suggesting that the same motivational strategies may not be universally effective. Understanding these differences is crucial for educators and policymakers aiming to implement effective motivational strategies that are culturally responsive.

In the specific context of this study on digital distractions in educational settings, the cultural perspective on motivation can significantly influence how students interact with technology and how it affects their learning. Extrinsic motivations might lead students to engage more frequently in cyberslacking behaviours if they prioritize external rewards over deep engagement with course material, which could result in increased use of mobile phones and other digital devices in the classroom (Wang et al., 2022b). Conversely, intrinsically motivated students may find greater internal satisfaction in learning activities, making them less prone to digital distractions and more focused during class sessions (Liao and Wu, 2022). This distinction is key to developing targeted strategies that help manage digital distractions effectively, ensuring they support rather than hinder academic achievement in diverse educational environments.

2.3.3. *Long-Term Orientation*

The influence of cultural values on educational outcomes and the role of technology in learning has been well-documented in the literature. Hofstede's cultural dimensions theory provides a robust framework for understanding how national cultural norms can shape individual and group behaviours in the academic setting (Hofstede, 2001a; Alqarni, 2022). This study will focus on the Long-Term Orientation dimension from Hofstede's framework, which reflects a society's focus on the future versus the past and present.

Hofstede's Long-Term Orientation dimension reflects the degree to which a culture values long-term, future-oriented thinking versus short-term, traditional perspectives (Hofstede, 2001a; Hollender et al., 2010a). Cultures high in Long-Term Orientation tend to be more pragmatic, adaptable, and focused on long-term results. In contrast, low Long-Term Orientation cultures emphasise maintaining traditions and achieving immediate gratification. In the educational context, the Long-Term Orientation dimension may influence how students approach their studies and manage digital distractions. Students from high Long-Term Orientation cultures may be more likely to prioritize long-term academic success and view digital distractions as a hindrance to their future goals (Lindström, 2020; Wang et al., 2022a). Conversely, students from low Long-Term Orientation cultures may be more inclined to prioritize short-term pleasure and indulgence, potentially leading to increased susceptibility to cyberslacking behaviours (Sirois, 2022).

Long-term oriented cultures emphasize values such as perseverance, thrift, and adaptability, whereas short-term oriented societies are more concerned with upholding tradition and immediate gratification (Hollender et al., 2010a). This cultural orientation has been linked to students' academic motivation, study habits, overall performance, technology use, and susceptibility to distractions (Hofstede, 2011; Taylor et al., 2023). Research has shown that students from more long-term oriented countries are more likely to enrol in advanced college-level classes, have better school attendance records, and are less likely to repeat a grade or be truant (Figlio et al., 2024). This suggests that the cultural value of long-term orientation may play a significant role in shaping students' academic behaviour and achievement.

2.4. Gaps in Current Literature Regarding Cultural Influences

In the exploration of the impact of digital distractions on academic performance among university students, specifically focusing on phone usage patterns within the learning environment, a detailed review of the existing literature underscores significant gaps, particularly in the context of cultural influences. This narrative elucidates these gaps, advocating for a more culturally nuanced understanding of digital distraction. The research field predominantly concentrates on Western or individualistic cultural contexts, significantly neglecting the potential variability and uniqueness of digital distraction phenomena across diverse cultural backgrounds (McSweeney, 2002; Papaioannou et al., 2023). This oversight raises questions about the applicability and generalizability of such findings to non-Western or collectivist cultures and ignores the distinct social dynamics, educational practices, and technological engagements that characterize these societies.

Furthermore, while an emerging body of work examines broad digital device usage patterns across various cultures, there is a marked deficiency in studies that delve into the nuances of phone location habits during study sessions. The differential management of devices between individualistic versus collectivist cultures could provide critical insights into strategies for minimizing distractions, yet this area remains largely unexplored (Morris et al., 2015). Another significant gap in the literature is the lack of investigation into how cultural values—such as restraint versus indulgence—may moderate the relationship between digital distractions and academic outcomes. This omission suggests a need for research that considers how deeply embedded cultural values influence students' engagement with digital devices and, by extension, their academic performance (Hofstede, 2001b).

Additionally, the role of developmental and generational factors within different cultural contexts has been underexamined (Kertzer, 2019). Assumptions that younger, so-called "digital native" students are universally more prone to distraction overlook the potential influence of cultural upbringing and values on this relationship. Equally, there is a scant examination of the influence of specific cultural norms around technology use, communication styles, and educational goals on digital distraction. Investigating how contrasting cultural traditions in technology and education might affect students' engagement and distraction levels could offer profound insights.

Similarly, the literature has yet to fully address the differences between oral and literate cultural traditions regarding learning approaches and technology integration. This gap suggests an area ripe for research, potentially revealing how traditional educational practices influence students' interactions with digital technologies and their susceptibility to distractions (Henderson, 1996). Methodologically, the field suffers from a reliance on studies utilizing samples drawn exclusively from single cultures rather than adopting comparative designs that span multiple cultural settings (Fyhn et al., 2016). This methodological limitation severely constrains the depth of understanding regarding how cultural factors might influence digital distraction patterns among students. Lastly, a notable lack of theory-driven research applies established cultural models, like Hofstede's dimensions, to analyze digital distraction (Hofstede, 2001b).

Incorporating such theoretical frameworks could provide a structured basis for investigating the complex interplay between cultural contexts and digital distractions. The current literature points to a critical need for comprehensive, cross-cultural research in this area. By addressing the outlined gaps, future studies could significantly advance our understanding of how cultural contexts shape the causes and impacts of digital distractions. This advancement is crucial for developing more effective strategies to minimize the adverse effects of digital distractions on academic achievement, paving the way for educational environments more conducive to learning in an increasingly digital world.

2.5. *Theoretical Frameworks Incorporating Cognitive Load Theory*

Investigating the phenomenon of digital distractions, particularly the usage patterns of phones within educational settings, through the prism of Cognitive Load Theory (CLT), unveils a multifaceted perspective on the challenges university students encounter in optimizing their academic performance. With its foundational emphasis on the limitations of working memory, coupled with the delineation of cognitive load into intrinsic, extraneous, and germane types, CLT offers an expansive framework for dissecting the intricacies of learning amid the pervasive influence of digital distractions. At the heart of CLT lies the principle of intrinsic cognitive load, which remains a constant entity inherently tied to the complexity of the educational content itself. Conversely, the extraneous cognitive load, susceptible to variations induced by the instructional design and the broader learning environment, presents a dynamic aspect of cognitive load management. The advent and integration of digital technologies within educational paradigms, especially the widespread utilization of smartphones, have ushered in novel sources of extraneous cognitive load previously uncharted in conventional learning environments. This evolution is underscored by the research of Hollender et al. (2010b), who expanded the scope of extraneous cognitive load to encompass the demands imposed by software interfaces, thereby highlighting the augmented cognitive load borne from engagements with digital platforms.

Further delving into the nuances of extraneous cognitive load, Skulmowski and Rey (2020) advocate for a granular dissection of extraneous load into discrete categories, such as those engendered through software interactions, advocating for a recalibrated approach towards managing cognitive load within digital learning ecosystems. This call for specificity is echoed in the work of Andersen and Makransky (2021), who pioneered cognitive load surveys tailored for virtual reality learning environments and dissected extraneous load into instructional, interactional, and environmental subcomponents. This refined approach to cognitive load measurement mirrors the complex interplay between digital distractions and cognitive load, underscoring the multifaceted extraneous load that digital distractions, including phone usage, impart on the learning process.

The interconnection between cognitive load and neuroscience provides an insightful lens into the neural underpinnings of cognitive load, as elucidated by Whelan (2007). This research trajectory aligns extraneous load with the disruption of attentional modulation mechanisms, positing that digital distractions, by inflating extraneous cognitive load, encroach upon the cognitive reserves allocated for assimilating educational content. This perspective posits digital distractions as perceptual barriers, vying for the limited attentional resources essential for efficacious learning. The debate between cognitive costs, represented by extraneous load, and the benefits encapsulated in germane processing, is artfully navigated through the cost-benefit model articulated by Skulmowski (2023). This model encapsulates the delicate equilibrium between harnessing the engaging potential of technology and mitigating the attendant increase in cognitive load for a decrement in learning efficiency.

In essence, the application of CLT to the exploration of digital distractions in learning environments underscores a pivotal equilibrium between managing cognitive load and capitalizing on the educational affordances of digital tools. This theoretical vantage point not only fosters a deeper comprehension of the cognitive dynamics at play but also steers the conceptualization of instructional designs and pedagogical strategies to minimise distractions and maximise learning outcomes. As digital technologies become increasingly ingrained in educational contexts, the insights gleaned from CLT and its relevance to digital distractions are paramount for educators, instructional designers, and academic researchers, guiding the evolution of learning environments that adeptly balance the lure of digital engagement with the imperative of cognitive efficiency.

2.6. *Hypothesis Development*

Building upon the comprehensive review of the literature, which intricately explores the interplay between CLT and the pervasive influence of digital distractions within educational environments, this study aims to empirically investigate the nuanced impacts of such distractions on academic performance. Through the lens of CLT, we delve into the complexities of how smartphone interactions during study sessions influence students' learning outcomes. The analysis examines the role of cultural backgrounds and disciplinary fields in modulating these effects, aiming to provide insights into the broader implications of digital distractions across diverse educational contexts. This investigation is structured around hypotheses that seek to unravel the correlations between digital proximity, cultural variations, and their collective impact on students' academic achievements, thereby enriching our understanding of the contemporary digital learning landscape.

- $\mathbf{H}_1$: The impact of phone location on performance is moderated by long-term orientation, suggesting that the relationship between phone location and performance varies based on levels of long-term orientation.
- $\mathbf{H}_2$: The relationship between phone location and performance is moderated by motivation levels, indicating that the effect of phone location on performance changes with differing motivation levels.

- **H**$_3$: The effect of phone location on performance is moderated by indulgence levels, proposing that individuals with varying indulgence levels experience different performance outcomes from the same phone location contexts.
- **H**$_4$: The influence of phone location on performance is moderated by age, suggesting that the geographic or situational context's impact on performance differs across age categories.
- **H**$_5$: The association between phone location and performance is moderated by university quality, indicating that the effect of geographic or situational context on performance varies with the quality of the university attended.
- **H**$_6$: Phone location directly influences performance, demonstrating that the geographic or situational context, as reflected by phone location, has a measurable effect on performance outcomes.
- **H**$_7$: The relationship between phone location and performance is further moderated by factors such as long-term orientation, motivation, indulgence, age, and university quality, suggesting that the impact of geographic or situational context on performance is complex and influenced by a range of individual characteristics and demographics.

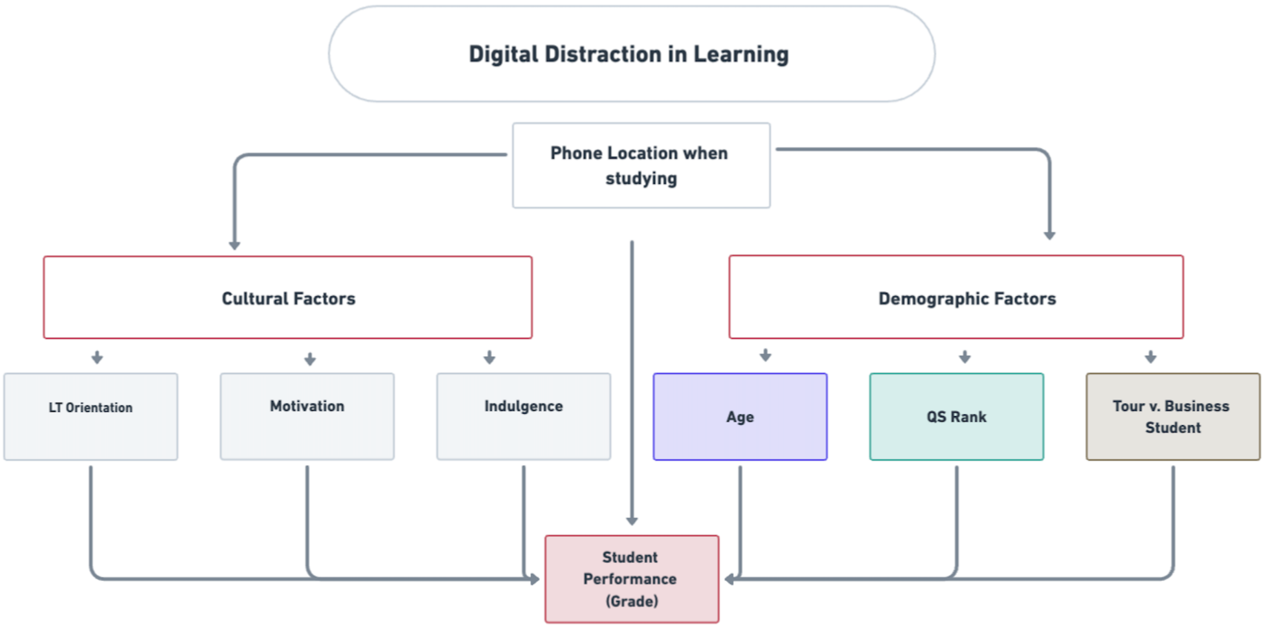

Figure 1: Flow Chart

3. Methodology

3.1. Data Source

In this investigation, conducted from June 2023 to March 2024, we examined the demographic and academic characteristics of 389 university students from Taiwan and Vietnam, employing an online survey methodology that was both voluntary and comprehensive. Despite the survey's location being anchored in Taiwan and Vietnam, participants hailed from diverse national origins, enriching the study's cultural breadth. The age spectrum of respondents was predominantly youthful, with 59.64% aged between 18 and 20 years, extending to a smaller group over 30, illuminating the study's focus on a younger demographic. Geographical diversity was marked, with 74.29% of students from Taiwan and 25.71% from Vietnam, showcasing a significant majority of the sample residing in Taiwan. Academically, the cohort was predominantly undergraduate (95.63%), with a minority in master's programs (4.37%), focusing on Business (35.73%) and Hospitality and Tourism (64.27%). This academic landscape is pivotal for assessing the influence of the field of study on digital distractions. Interestingly, the QS ranking of the universities from which participants were drawn varied, with 25.71% attending a university ranked 140th globally, 10.03% at a rank of 505, and a notable 64.27% from institutions not ranked (NA), suggesting a wide range of educational environments. Inspired by previous research paradigms, this study's methodology utilized incentives to ensure complete participation, aiming to deepen the discourse on technological distractions in academic settings through a nuanced understanding of students' digital engagement across different educational and cultural contexts.

The data collection phase of the study delved into the positioning of mobile phones during study sessions as a proxy for assessing potential distraction sources among university students. Participants reported their usual phone locations, ranging from "In another room" to "Actively used for study," including options for both visible and immediate accessibility, such as "Face up next to me" and "Face down next to me," as well as "No consistent pattern" for those with variable habits. The findings highlighted a predominant tendency to keep the phone within easy reach, with 40.26% of students having their phones face up next to them and 24.36% with them face down beside them. Notably, 11.54% of students indicated using their phones actively for study purposes, while 19.49% reported no consistent placement pattern, reflecting diverse approaches to phone-induced distraction management. Only 3.59% preferred keeping their phones in another room, underscoring the prevalent desire for close phone proximity. This investigation into physical phone placement complements the broader inquiry into technology-based distractions. It examines how students interact with their devices during academic activities and their self-management strategies in maintaining focus amidst potential digital interruptions. Through this comprehensive exploration, the study aims to shed light on the nuanced ways in which technology permeates the academic experiences of university students, offering insights into their behavioural patterns and the implications for educational engagement and distraction mitigation strategies. Table 1 presents a structured overview of survey data collected from various respondents, categorized by their origin, age group, field of study, and the QS ranking of their institutions.

Table 1: Detailed Summary of Respondent Demographics and University Rankings

Nationality			Age Category			Study Field			QS Ranking		
Category	n	Pct.	Category	n	Pct.	Category	n	Pct.	Category	n	Pct.
American	1	(0.26%)	18 - 20	232	(59.64%)	Tourism	250	(64.27%)	140	100	(25.71%)
French	5	(1.29%)	21 - 22	92	(23.65%)	Business	139	(35.73%)	505	39	(10.03%)
German	6	(1.54%)	23 - 24	35	(9.00%)				NA	250	(64.27%)
Other	27	(6.94%)	25 - 26	6	(1.54%)						
Taiwanese	245	(62.98%)	27 - 30	2	(0.51%)						
Vietnamese	105	(26.99%)	30+	7	(1.80%)						

Note: The education level of the study participants is split as follows: high school (2.7%), college (15.5%), bachelor's (43.7%), masters (34.4%), and Ph.D. (3.5%)

The descriptive statistics presented in the Table 2 outline a comprehensive analysis of various factors influencing student performance, categorized into dependent and independent variables, along with demographic and cultural mediators. The focal point, student performance (graded out of 100), exhibits an average score of 80.35 with a standard deviation of 12.47 across 387 observations. This suggests a relatively high-performance level among the students. The performance data displays a slight negative skewness (-0.82), indicating that most students score above the mean, with a kurtosis of 3.16 pointing towards a modest peak in the distribution of grades. Figure 2 visually presents the distribution of grades by age category, while Figure 3 presents the phone location analysis by age category.

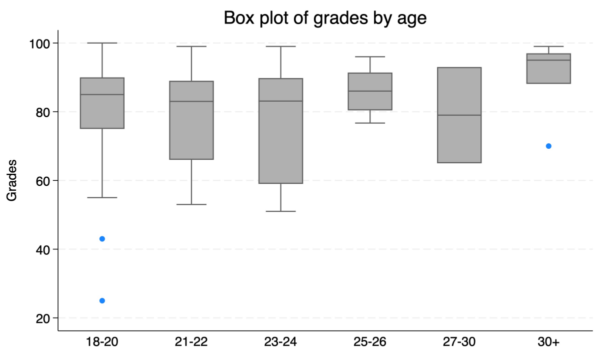

Figure 2: Grades Distribution

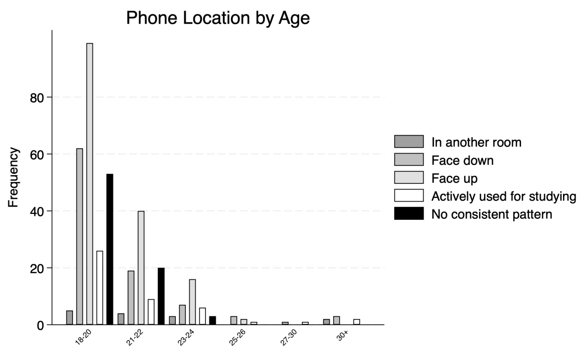

Figure 3: Phone Location Analysis

The analysis further investigates the impact of phone location during study sessions, categorized from the phone being in another room to being used for studying, reflecting varied study habits among students. In terms of demographic mediators, nationality shows a mean of 1.70 with a moderate standard deviation, implying diversity in student origins. The QS ranking of universities attended by students averages at 2.38, indicating participation from institutions of varying standings. Age is also considered, with students falling into various categories, showcasing the diverse age range of participants. Based on Hofstede's cultural dimensions, cultural mediators delve into aspects like motivation, long-term orientation, and indulgence, with scores suggesting significant cultural influences on student attitudes and behaviours. These comprehensive statistics paint a vivid picture of the multifaceted factors in determining student performance, highlighting the role of study environment, demographic backgrounds, and cultural orientations.

Table 2: Descriptive Statistics

Variable	Definition	Mean	SD	Obs	Min	Max	Skew.	Kurt.
Dependent Variable								
Perform	Student course grade out of 100	80.35	12.47	387	25	100	-0.82	3.16
Independent Variable								
Phone Location	Phone location while studying.							
1	Phone in another room	0.04	0.19	387	0	1		
2	Phone Facedown	0.25	0.43	387	0	1		
3	Phone Face up	0.41	0.49	387	0	1		
4	Phone used for studying	0.12	0.32	387	0	1		
5	No consistent pattern	0.20	0.40	387	0	1		
Demographic Moderators								
Tour v Biz.	Binary program code	1.36	0.48	387	0	1	-0.59	1.34
QS_Rank	Worldwide university ranking	2.38	0.87	387	1	3	3.38	12.41
Age	Categorical variable of student age	1.58	0.97	387	1	6	2.35	9.72
Cultural Moderators								
Motivation	Hofstede's 3rd cultural dimension	43.94	3.99	360	40	68	3.66	23.67
LT Orient.	Hofstede's 5th cultural dimension	74.36	18.35	360	47	87	-0.78	1.63
Indulgence	Hofstede's 6th cultural dimension	44.81	6.49	360	35	68	-0.71	2.11

The correlation matrix, as seen in Table 3, provides an intricate snapshot of the relationships between various academic and demographic variables in relation to student performance. Notable strong positive correlations include student performance with QS_Rank (0.797*), suggesting that higher university rankings are associated with better student outcomes. Indulgence (0.737*), indicating that greater indulgence scores may contribute positively to academic success. Conversely, a significant negative correlation is observed between student performance and the Tour_Biz variable (-0.697*), implying a possible inverse relationship between fields related to tourism and business and academic achievement. The matrix also highlights the impact of phone location (PhneLoc) on performance, with a modest but significant positive correlation (0.156*), suggesting that certain phone placement strategies during study sessions may facilitate better grades. Demographic variables, such as nationality (Nation_1, Nation_2, etc.), show varied correlations with performance, reflecting the complex influence of cultural and national backgrounds on educational outcomes. Significantly, the matrix elucidates the nuanced interplay between academic metrics, student behaviours, and demographic factors, offering valuable insights into the determinants of educational success.

Table 3: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	**Perform**	1												
2	**PhneLoc**	**0.156***	1											
3	**Age**	-0.016	-0.128	1										
4	**QS_Rank**	**0.797***	**0.238***	**-0.182***	1									
5	**Tour_Biz**	**-0.697***	**-0.243***	**0.222***	**-0.951***	1								
6	**Nation_1**	**0.594***	**0.193***	**-0.265***	**0.832***	**-0.805***	1							
7	**Nation_2**	**-0.758***	**-0.208***	0.135*	**-0.892***	**0.742***	**-0.793***	1						
8	**Nation_3**	0.095	-0.059	**0.270***	-0.055	**0.168***	**-0.163***	-0.077	1					
9	**Nation_4**	0.013	-0.081	0.050	-0.050	**0.153***	**-0.149***	-0.070	-0.014	1				
10	**Nation_5**	0.032	0.037	**0.232***	-0.022	0.068	-0.066	-0.031	-0.006	-0.006	1			
11	**Nation_6**	**0.138***	0.053	0.067	0.031	0.070	**-0.356***	**-0.167***	-0.034	-0.031	-0.014	1		
12	**Indulg.**	**0.737***	**0.224***	**-0.165***	**0.905***	**-0.807***	**0.933***	**-0.972***	-0.097	0.059	**0.189***	-	1	
13	**Motiv.**	**0.518***	0.089	**0.173***	**0.479***	**-0.317***	**0.382***	**-0.636***	**0.787***	-0.028	**0.239***	-	**0.522***	1
14	**LT-Orient.**	**0.729***	**0.230***	**-0.247***	**0.929***	**-0.864***	**0.995***	**-0.958***	-0.123	-0.093	-0.070	-	**0.954***	**0.445***

Note: * $p<0.01$. Nation codes: 1 = Taiwanese, 2 = Vietnamese, 3 = German, 4 = French, 5 = American, 6 = Other.

3.2. *Methodology*

In this study, we utilized Structural Equation Modeling (SEM) within Stata to examine the effect of phone location on academic performance, with an emphasis on identifying moderating factors such as long-term orientation, motivation, indulgence, age, and university quality. The analysis began with the precise organization of data, ensuring each variable—sourced directly from our dataset—was prepared to directly evaluate both the primary effect and the moderating influences. This methodological approach, centred on observed variables, diverged from conventional SEM applications that often focus on latent constructs, aiming instead to directly assess the influence of physical phone location and its interaction with various individual and institutional characteristics on academic outcomes.

The SEM analysis facilitated a dual examination: it tested the direct impact of phone location on academic performance and explored how this relationship might vary under the influence of the selected moderators. This approach allowed for an intricate analysis of the primary relationship and a detailed investigation into the conditions that might modify this effect. The outcome of this study is anticipated to offer insights into the interplay between technology usage and educational achievement. By uncovering the nuanced ways in which individual characteristics and contextual factors can influence the relationship between digital behaviour and academic performance, the study seeks to contribute to the development of strategies that enhance student performance in the context of digital learning environments.

4. Results

The results of the structural equation modelling, depicted in Figure 4, illustrate the complexity of factors influencing academic performance. Standardized path coefficients from the model (Table 4) reveal a nuanced landscape where phone location serves as a critical variable. Specifically, the phone location's direct path to academic performance yielded a coefficient of (-0.11), denoting a slight yet significant negative influence ($p < 0.05$), suggesting that more accessible phone locations may slightly detract from academic performance.

The coefficient for phone location's direct impact on performance is (-0.163) (Table 4), but it is not statistically significant ($p = 0.632$). This suggests that, within this model, the physical location of a phone (indicative of its accessibility or potential for distraction) does not significantly impact academic performance. However, the examination of moderators reveals a more nuanced picture.

Examining the moderators, long-term orientation ($LT_Orientation$) presented a substantial path coefficient of (-0.096) with a significance level of $p < 0.01$ (Table 4), indicating a negative influence on performance. Motivation ($Motivation$), shown by a coefficient of (0.165) with $p < 0.01$, also served as a moderator but had a relatively pronounced positive effect. This reflects that heightened motivation could significantly counterbalance the adverse effects of phone location on performance. Indulgence ($Indulgence$) indicated a slightly negative moderation (path coefficient of (-0.163) with $p < 0.05$), which suggests that indulgent tendencies might marginally amplify the distraction potential of accessible phones.

Age category ($AgeCat3$) showcased a significant positive path coefficient of 1.086 ($p < 0.01$), reinforcing the model's suggestion that certain age groups might be more resilient to the negative effects of phone location on academic output. Furthermore, the performance path to the *QS_Rank* variable stood out with a significant positive coefficient of 21.755 ($p < 0.001$) (Table 4), suggesting that students from higher-ranked universities may experience a reduced negative impact from phone location, possibly due to stronger institutional support structures or personal study strategies.

The model fit information (Table 5) shows that our SEM model provides a good fit to the data, with a BIC of 12579.65, AIC of 12472.77, and CAIC of 12606.65. These values suggest that the model adequately captures the underlying patterns in the data while maintaining a balance between model complexity and goodness of fit. Additionally, the SEM model's error terms, indicated as e_2 through e_6, varied in magnitude, with e_2 at 3.18 being the most significant, hinting at additional unexplained variance in the relationship between long-term orientation and phone location. Overall, the SEM output highlights that while phone location does have an observable negative effect on academic performance, this effect is subject to the influence of individual characteristics and contextual factors, as demonstrated by the varied path coefficients of the moderators in the study.

Table 4: SEM Analysis: Impact of Phone Location on Performance

Variable	Coefficient	Std. Err.	z-value	P-value
Perform ← LT_Orientation	-0.096	0.035	-2.75	0.006**
Perform ← Motivation	0.165	0.060	2.75	0.006**
Perform ← Indulgence	-0.163	0.067	-2.44	0.015*
Perform ← Age_Category	1.086	0.337	3.22	0.001**
Perform ← QS_Rank	21.755	1.365	15.94	<0.001***
Perform ← Tour_Biz	14.373	2.344	6.13	<0.001***
Perform ← Phone_Location	-0.163	0.340	-0.48	0.632

Note: Significance levels are denoted as $p < 0.001$ (***), $p < 0.01$ (**), and $p < 0.05$ (*). The absence of an asterisk indicates a lack of statistical significance.

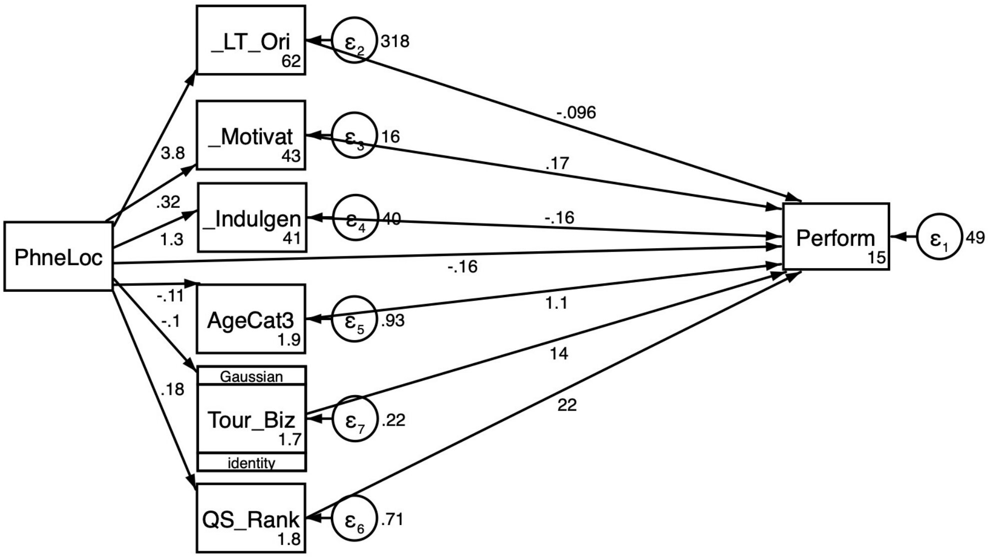

Figure 4: Structural model showing standardized path coefficients

Table 5: Model Fit Information

Model	N	ℓ(null)	ℓ(model)	df	AIC	BIC	AICc	CAIC
	387	–	-6209.385	27	12472.77	12579.65	12476.98	12606.65

Note: BIC - Bayesian information criterion, AIC - Akaike's information criterion, AICc - corrected Akaike's information criterion, CAIC - consistent Akaike's information criterion, ℓ is log-likelihood.

4.1. Robustness Test through Hierarchical Linear Modeling

Hierarchical Linear Modeling (HLM) was additionally employed to investigate the influence of individual-level predictors such as phone location, motivation, long-term orientation, and indulgence on academic performance across different national contexts. The utilization of HLM is particularly pertinent for our dataset, which exhibits a nested structure with students grouped by their national origins (Raudenbush and Bryk, 2002). This statistical approach is crucial for addressing the dependencies that naturally arise in multilevel data, allowing for the analysis of effects at multiple levels simultaneously (Raudenbush et al., 2019). Unlike conventional regression techniques, HLM provides a more sophisticated examination by partitioning the variance attributable to individual, school, or country-level predictors, thus offering a detailed understanding of how these variables interact to influence student outcomes (Hox et al., 2013).

The HLM analysis in this study aimed to assess both the fixed effects of our chosen predictors on academic performance and the potential variability of these effects across different cultural settings. By incorporating predictors at the student level and allowing for random intercepts and slopes at the national level, the model is designed to capture the unique cultural dynamics that might affect the relationship between individual behaviours and educational achievement (Lee, 2000). The statistical robustness of HLM also ensures that the estimated standard errors are more reliable, reducing the likelihood of aggregation bias that often plagues simpler analytical approaches (Lee, 2000).

Our findings from the HLM analysis, as reported in Table 6, highlight the significant impact of motivational factors (0.676) with $p < 0.001$) and LT. Orientation (0.287) with $p < 0.001$) on academic performance across national contexts, indicating that these traits are universally beneficial. However, the influence of phone location on academic outcomes appeared to be less consistent (-0.110) with $p = 0.780$), suggesting that its impact might vary significantly across different cultural or educational settings. These results underscore the complexity of disentangling the effects of individual behaviours within the broader cultural milieu.

Table 6: HLM mixed-effects model analysis results

Variable	Coefficient	Std. Err.	z-value	p-value
Phone.Location	-0.1097	0.3937	-0.28	0.780
Motivation	0.6761	0.1294	5.23	0.000
LT_Orientation	0.2874	0.0818	3.52	0.000
Indulgence	0.4463	0.2424	1.84	0.066
Random-effects Parameters	Estimate			
var(Phone.Location)	1.10×10^{-6}			
var(Motivation)	0.0000792			
var(LT_Orientation)	0.0004896			
var(Indulgence)	0.0040121			
var(_cons)	0.6660708			

Table 7: Mixed-effects Model Regression Analysis

Description	N	N groups (Nationality)	χ^2	ℓ	LR test vs. linear model: χ^2	$p > \chi^2$
Value	360	5	501.370	-1265.789	0.004	1.000

Note: Wald χ^2 indicates the chi-square statistic of the model. Log-likelihood (ℓ) shows the log of the likelihood function at its maximum. LR test vs. linear model provides a likelihood ratio test comparing the mixed model against a simple linear regression, indicating the complexity and fit improvement of the mixed model.

5. Discussion

This study, utilizing survey data from 387 respondents, explored the intricate relationship between the location of phones during study sessions and student performance, as measured through academic grades. Employing SEM, the research aimed to understand not only the direct effects of phone location but also how psychological and demographic factors potentially moderate these effects. Surprisingly, the direct impact of phone location on performance did not show statistical significance, indicating that the simple presence of a phone might not be as distracting as previously assumed. This finding challenges the straightforward application of CLT, which would predict that nearby phones inherently increase cognitive load and thus diminish learning potential.

HLM was subsequently employed to further investigate these relationships within a multilevel data structure, accounting for the nested influences of national origins. The HLM analysis revealed that while Motivation and LT. Orientation significantly enhanced performance across various national contexts, the impact of phone location was inconsistent, suggesting variability in its effect dependent on cultural or educational settings. These findings from the HLM regression, underscore the complexity of managing distractions within diverse educational environments and further challenge the assumptions of CLT regarding the universal impact of visible distractions.

CLT suggests that learning environments should minimize unnecessary distractions to optimize cognitive processing. In our study, however, factors such as the quality of the university (*QS_Rank*) and the field of study (*Tour_Biz*) significantly influenced how phone location impacts performance, suggesting that certain educational settings might effectively mitigate potential cognitive distractions. Moreover, long-term orientation had a positive effect, implying that students with future-oriented goals might possess better strategies for managing cognitive load, thus maintaining performance despite potential distractions. These results underscore the complexity of applying CLT in real-world settings, where various moderating factors can influence the relationship between environmental stimuli and cognitive load.

The model fit data further supports the complexity of our SEM model, capturing the nuanced interactions between phone location, student characteristics, and educational environment. The significant error terms, particularly e_2 at 3.18, indicate additional unexplained variance, hinting at other factors that might be affecting cognitive load and learning outcomes. This supports the CLT perspective that managing cognitive load is crucial but also complex, involving more than just managing visible distractions. It suggests that educational interventions need to consider broader aspects of cognitive load management, incorporating strategies that enhance intrinsic motivation and support effective cognitive strategies.

The implications of these findings extend beyond traditional applications of CLT, suggesting that educational settings can be designed to help students manage the potential cognitive load imposed by digital distractions. Rather than eliminating digital devices, which is often impractical, enhancing educational environments to support cognitive management strategies may be more effective. This approach aligns with recent interpretations of CLT that emphasize the importance of adaptive learning environments that respond to individual needs and contextual factors. As digital integration in education continues to evolve, understanding these dynamics becomes crucial for developing educational policies and practices that support effective learning.

6. Conclusion

Digital technologies, particularly smartphones, have become integral to the lives of young adults, leading to concerns about their impact on cognitive processes and academic outcomes (Wilmer et al., 2017; Flanigan and Babchuk, 2022). Our study offers a more detailed understanding of this issue within university contexts. Unlike previous research that reported direct negative effects of mobile devices on learning (Kuznekoff and Titsworth, 2013; Waite et al., 2018a), our additional findings from HLM did not reveal a significant impact of phone location on academic performance, suggesting that the mere presence of these devices does not necessarily impair student learning.

These results indicate that the proximity of digital devices might not be as disruptive to student learning as previously thought. CLT suggests that the extraneous cognitive load from nearby mobile phones does not automatically overtax students' cognitive capacity or hinder their engagement with academic material (Hollender et al., 2010a; Skulmowski and Rey, 2020). However, our analysis identified several moderating factors, such as institutional context, academic discipline, and individual differences, with the cultural factors of Motivation (0.676, $p < 0.001$) and Lt.Orientation (0.287, $p < 0.001$) playing significant roles in moderating these effects.

This research contributes to the evolving discourse on digital distractions in educational settings by underscoring the importance of cultural factors and individual attributes like motivation and long-term orientation. While prior studies have predominantly focused on the negative impacts of technology in classrooms, our findings advocate for a culturally informed approach to understanding how digital distractions affect learning in various educational contexts. Therefore, we recommend that interventions and policies addressing digital distractions adopt a culturally responsive and comprehensive strategy that not only limits device usage but also enhances students' self-regulatory skills and cultural awareness to help them thrive in environments rich with digital technologies.

As digital tools increasingly infiltrate educational settings, it becomes essential to grasp the complex dynamics of digital distractions within these culturally diverse frameworks. Our study highlights that universal solutions are not always effective and that addressing technological educational challenges requires nuanced, culturally sensitive strategies. By acknowledging and integrating cultural differences and motivational factors into educational practices, educators and policymakers can devise more effective measures to enhance student focus and academic success in the digital era.

6.1. Limitations and Direction for Future Research

While robust in its examination of digital distractions within specific educational and cultural settings, this study encounters several limitations that necessitate cautious interpretation and guide future research avenues. The focus on university students from Taiwan and Vietnam restricts the unreliability of findings across diverse educational systems and cultural contexts, and reliance on data collected within a fixed time frame (June 2023 to March 2024) might not accurately reflect evolving digital habits or long-term trends. Furthermore, the study's use of self-reported data could introduce biases such as social desirability or recall inaccuracies. Future studies should aim to broaden the cultural and geographic scope by including a more diverse range of participants, perhaps from countries like the U.S., China, and African nations, to enhance cross-cultural insights into digital distractions. Longitudinal research is recommended to uncover how relationships between phone usage, cultural factors, and academic performance develop over time. Additionally, integrating objective measures like application usage data or digital screen time tracking could complement self-reported information, providing a more accurate depiction of phone usage behaviours. There is also a need to explore the roles of educational policies, teaching practices, and institutional support structures in mitigating the impact of digital distractions. Moreover, developing and empirically testing culturally informed interventions could help enhance students' digital literacy and self-regulation skills, potentially improving academic outcomes in digitally integrated learning environments.

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