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DIGITAL LEARNING FATIGUE AND STUDENTS' LEARNING MOTIVATION: A DESCRIPTIVE- CORRELATIONAL STUDY

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ABSTRACT

This descriptive-correlational study determined the relationship between digital learning fatigue and motivation for learning among 130 tertiary students at West Visayas State University – Himamaylan City Campus. The research was set under the condition of long-term online learning since most infrastructure and environmental conditions in reporting a very high heat index and inadequate physical facilities meant students had to stay under the digital learning modalities. The validated researcher-made tools have been constructed to measure levels of digital learning fatigue and motivation to learn. Findings show that students experienced a moderate level of digital learning fatigue and had moderate motivation to learn. It was also noted that even though senior students and others taking particular disciplines had slightly higher levels of fatigue, the analysis indicated no statistically significant differences of fatigue and motivation when the respondents were grouped according to age, year level, or course taken. The Spearman's rho test showed a low negative but statistically non-significant correlation between digital learning fatigue and motivation to learn ($\rho = -0.119$, $p = .171$). This suggests that, even though students are involved in digital fatigue, that situation-their motivation-is not significantly different, which might mean that external support, resilience, or other contextual factors might act as mitigators of external influence. Such findings highlighted the need to address both technological and environmental considerations in rural campuses especially on digital learning outcomes and policy development.

INTRODUCTION

Digital learning has been extensively studied over the past several years, especially in relation to higher education. In the teaching and learning process, technology can replace traditional teaching with respect to how students access content, interact with teachers, and engage in academic studies. Online learning platforms like Google Classroom, Zoom, and Moodle are now universal tools in different disciplines. Online education provides flexibility, efficiency, and greater access to educational resources (Dhawan, 2020). Pretty recently, the social and health implications of using technology in the education process have gained attention as one of the major problems (Dian, et al., 2020). Digital learning fatigue (defined as mental fatigue, decreased concentration, and disengagement) is a recent, widespread phenomenon that involves spending more time on screen and engaging more often online (Pepper et al., 2021). Digital learning fatigue may adversely affect a student's "learning motivation"–a major driver of academic performance and persistence in higher education (Nadler, 2020).

Another vital factor affecting the motivation of students to learn in online environments is the existence of environmental and infrastructural issues. In most rural or underdeveloped regions, students are forced to engage in online learning not by choice but because there are no safe and operational school buildings or inappropriate classroom conditions resulting from extreme temperatures. Research has established that extreme heat index levels have been known to hamper the cognitive functioning and learning capabilities of students, rendering physical learning environments ineffective or even dangerous (Park et al., 2020). Further, insufficient electricity, reliable internet, and computing devices in such areas aggravates stress and limits students' capacity to remain focused on studies (Olum et al., 2020). The blending of physical discomfort and technological constraints can lead to decreased academic motivation, given that students are unable to stay focused, disciplined, and interested in learning under such restrictions.

In the research literature on digital learning fatigue, few studies have examined the effects of digital learning fatigue in academic settings where online learning is not persistent just due to a global health crisis but because of institutional or environmental constraints. These studies are often not satisfying because they tend to be focused exclusively on urban institutions that offer hybrid or face-to-face learning. One question that would be interesting to answer, however, is how prolonged exposure to online learning – beyond the period of emergency – would affect students who are forced to remain online due to insufficient infrastructure or heat-related classroom unavailability. For example, in some developing regions, including rural campuses in the Philippines, face-to-face learning has been suspended because of inadequate school buildings or due to extreme classroom conditions, creating a unique digital learning setting that is not currently studied in the literature.

This study aimed to determine the relationship between digital learning fatigue and learning motivation among selected students of West Visayas State University–Himamaylan City Campus, using simple random sampling. It also sought to examine whether the prolonged duration of online learning—caused by limited infrastructure and the unavailability of classrooms due to a high heat index—adversely affects students' motivation.

REVIEW OF RELATED LITERATURE

The term digital learning fatigue is based on two fundamental foundations. Digital come from the Latin word digitus (Harper, 2022), which was used to denote numerical systems (in contrast to computer technology in the 20th century), learning comes from the Old English word leornian ("to get knowledge, be cultivated") (Oxford English Dictionary, 2023). Fatigue comes from the Latin word fatigare ("to tire out" or "exhaust"). Incorporated, digital learning fatigue is the state of mental, emotional, and physical exhaustion as a result of extended exposure to digital learning environments. Digital learning fatigue is defined broadly as a psychological and physiological state of tiredness or burnout induced by continued exposure to digital screens and online learning environments (Lee et al., 2021). Common findings in learners participating in extended online education have been documented as decreased attention span, demotivation, eye strain, and emotional exhaustion.

Wiederhold (2000) defines digital fatigue as "a kind of burnout based on excessive virtual interactions", and it is characteristic of "online classes, virtual meetings, and constant digital learning". Digital learning fatigue is also frequently observed when students are compelled for extended periods of remote learning, such as in this case, due to the COVID-19 pandemic. According to Wang et al. (2021), 68% of university students reported moderate to severe levels of digital learning fatigue, as a result of the transition to remote learning. It suggested that digital learning fatigue emerged from: - "excessive screen time - minimal face-to-face interaction - poor ergonomic surroundings" when participating in home based learning Another study, Pandya & Lodha (2021), found that "digital fatigue significantly influences students' feelings of burnout, anxiety, and academic neglect", "and also contributes to their disengagement from their studies". The implications of digital learning fatigue are significant: "longer exposure to screens results in changes in posture affecting breathing capacity and stress levels, which can increase tension and limit cognitive performance." Remember, the signs and symptoms of digital learning fatigue cannot only be subjective, but they can be detected. Their research suggests that digital learning fatigue may significantly contribute to poor learning outcomes, attention, motivation, and mental well-being.

In some cases, long-term online education has been proven to present unique academic, psychological and physical challenges for students; while online learning offers flexibility and access, there are several possible causes for fatigue, stress and decrease engagement when learning can be undertaken for a prolonged period. One big cause is too much screen time, as this has been linked widely to digital eye strain, headaches, and a decreased ability to focus. In their finding (Colley et al., 2021), too much exposure to digital screens during online classes increases the risk of visual fatigue and musculoskeletal issues, especially in students who don't have proper ergonomic settings at home. Another reason is the lack of social interaction. Due to the prolonged learning online students often feel isolated. They lack encounters with other students face-to-face where they can ask questions, get support and talk to peers. As Bao (2020) argued the lack of in-person interaction damages motivations and emotional support mechanisms for students and the perceived feeling of loneliness and disconnection from learning. Cognitive overload may also contribute to this problem. Because online learning environments often require students to process large amounts of information in relatively small-time frames, learning becomes mentally exhausting. Gonzalez et al. (2020) report that students who were given prolonged remote instruction experienced greater cognitive strain due to their need to be multitasking and working with multiple digital media at once. Moreover, technical problems and digital inequality are other major concerns. Not all students can access stable internet connections or reliable devices which can affect their learning and stress levels. As of 2020 's Adedoyin and Soykan 's the technological barriers bring to light that the continuity of online learning is significantly limited especially in developing countries which can impact on learner frustration and dropout rates. Lastly, lack of time management and regularity in online learning experiences has been shown to negatively affect student productivity and well-being. Without proper schedules many students find it difficult to follow an irregular sleeping pattern and improve their academic performance (Dhawan, 2020).

Digital learning fatigue has arrived globally, but its effects are most acutely experienced within developing contexts where technological, economic, and educational disadvantages enhance the challenges of prolonged digital education. Students in developing countries are faced with unique stressors that exacerbate fatigue such as limited access to digital infrastructure, unstable internet availability, and a deficiency of digital literacy. In the majority of developing countries, unequal access to technology is a structural problem. Adedoyin and Soykan (2020) pointed out that distance learning during the COVID-19 pandemic exposed deep digital divides, as poor or rural students struggled with a lack of devices and poor network connectivity. These constraints not only hinder learning but also cause frustration and disengagement, two of the most important indicators of digital fatigue.Moreover, domestic environments in low-income nations usually lack facilitating learning spaces. According to Onyema et al. (2020), most students have to share a device with their family members and study in noisy, populous homes where it is difficult to concentrate and be constantly

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engaged with digital content. This leads to mental stress, exhaustion, and eventually digital learning fatigue.

Deficits in digital literacy also contribute significantly. In a study by Muthuprasad et al. (2021), a few students from rural Indian communities complained of not being able to use learning management systems and online resources, putting cognitive load and stress on the learning process. The unfamiliarity with technology decelerates the learning process and imposes emotional exhaustion, particularly on first-generation college students.Additionally, infrastructural issues like interrupted power supply and constant connectivity disconnections aggravate fatigue due to the unreliability of participation online (Olum et al., 2020). Frequent interruptions contribute to stress and anxiety of being left behind lessons, which influences academic performance as well as wellness. Finally, scarce institutional support and the absence of culturally relevant content online cause students to become disengaged from the learning experience. In most instances, the teachers are not also well versed in digital pedagogy, and the instruction is ineffectual while there is heavy reliance on passive learning methods such as extensive video lectures and unnecessary reading materials that hasten exhaustion (Chakraborty & Nafukho, 2021).

Motivation is a significant psychological construct relevant to education. It is what drives goal-directed behavior (Schunk et al., 2014). Two varieties of such behavior exist simply because one wants to according to a theory known as Self-Determination Theory (Deci and Ryan, 2000). Something is done because it feels pretty great or curiosity gets piqued or learning becomes a necessity somehow suddenly. That's intrinsic motivation. Extrinsic motivation, on the other hand, is what drives you when you're doing something for a reward, a deadline, or to impress others. In a classroom, both of those kinds of motivators are influenced by how teachers interact with students, by group discussions—and by the overall structure of the learning environment. As Nadler (2020), notes, "distance from peers and impersonal nature of online communication can lower intrinsic motivation to learn. And extrinsic motivators don't work as well when students are disengaged or overwhelmed so less engagement and persistence.

Digital fatigue (mental exhaustion, irritability, and reduced cognitive function from screen time) affects students' motivation in online learning. One of the fastest-growing and most obvious effects of digital fatigue is the decrease in student attention spans. As Peper et al. (2021) explain, screen time demands continuous visual and cognitive demands on the brain that generate brain fatigue much faster than it does in person (and it does so very quickly). This attention deficit decreases dramatically. This decrease in focus directly impacts student ability to understand and retain information. While the latter effect may actually lead to poorer engagement, it significantly undermines learning outcomes.

Digital fatigue also negatively influences perceived academic self-efficacy—the student's belief that they have the capacity to complete learning tasks effectively. As Wang and Zhao (2022) noted, students who perceived to have a high degree of digital fatigue were less likely to believe that they were competent to address college-level work—even if they had previously been successful at doing so. This feeling of loss of control harms intrinsic motivation, possibly leading to feelings of helplessness and academic burnout. As digital fatigue develops, students tend to develop avoidance behaviors, such as procrastination or lack of participation when online sessions occur. "While the emotional distance and repetitive nature of digital learning environment may contribute to disengagement, especially when participants lack timely feedback or interaction with instructors, " noted Nadler (2020). "In addition, cognitive fatigue declines the motivation to initiate and sustain goal-oriented activities, leading to academic withdrawal and low course completion rates" (Wang & Zhao, 2022).

With increased awareness of the psychological effects of digital fatigue on motivation, many studies have focused more on students from provincial or rural campuses where, like WVSU-Himamaylan, there are less resources to help students manage their digital fatigue, most notably lack of infrastructure. Students at campuses like WVSU-Himamaylan face not only physical and emotional difficulties of the digital fatigue stigma but also lack of essential infrastructure such as dependable electricity and high-speed internet. We look at the effect of digital fatigue on the environment and assess learners' functioning in a range of setting: ventilation, high heat index, and poor connection are all common to consider when trying to manage student digital fatigue. It is hard to ignore the role of the environmental and infrastructural limitations of WVSU-Himamaylan, as these shortcomings have been ignored and reduced in the discussion around digital fatigue which tends to focus on more urbanized or well-resourced academic settings. The particular limitations of student learning in these provincial campuses (in which the disadvantages of digital environments are not health-related, but infrastructure constraints) need to be addressed in more focused research, and this research endeavor is to bridge this gap by providing evidence for the association between digital learning fatigue and student motivation in these under-resourced educational contexts.

A variety of environmental factors affecting learning contribute to motivation, engagement and academic achievement of students. In rural and provincial campuses, such as rural or provincial campus climate, building design and infrastructural factors, can increase digital learning fatigue and reduce the overall experience of digital learning for students. Heat influences cognitive performance in two ways. More generally, heat affects mental capacity. Exposure to heat has a direct impact on the functioning of cognitive processes, such as memory, concentration, and problem solving. Studies have found that high atmospheric temperatures lead to mental fatigue and an impaired focus on high-level problems (Zhang and colleagues, 2021). However, in tropical environments where air conditioning may

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not be available or cost prohibitive, students are left with the responsibility of learning in environments where their physical discomfort may compete with their abilities to think (Chaudhury et al., 2020). With this in mind, the high heat index of places such as the Philippines, where extreme humidity and high temperatures are common, is another barrier to effective learning — especially in digital formats, which require longer periods of time in front of screens. As Adhikari et al. (2017) point out, cognitive overload can be seen as a result of student pressure to engage in high-heat study environments which may adversely affect learning outcomes.

Educational buildings' design intricately influences learning effectiveness within their walls pretty significantly for occupants obviously. Unprotective artificial lighting and insufficient natural light alongside poor thermal insulation can hinder students focusing on learning activities quite badly. Classrooms without proper ventilation and inadequate insulation may experience exhaustion and high temperatures that make it difficult for students to concentrate for long periods (Altan & Everington, 2020). Environmental discomfort is particularly important when providing online learning where the student is expected to use their home or surrounding environment for education. The poor building design in rural areas (WVSU-Himamaylan for example) in times when infrastructure development is slower than in urban areas means that most students experience less-than ideal facilities which can lead to disruptive, uncomfortable experience and consequently lack of engagement. Absence of ergonomic physical frameworks as well as technological comforts that aid learning in rural campuses indicates the need for more advanced education architecture that considers the holistic health, mental, psychological, and physical needs of students. Such an issue is rare in the literature of educational research which primarily pays attention to well-off urbanized areas (Barker et al., 2017).

Equity in education is one of the most significant concerns in relation to the disparities that exist between rural and provincial campuses when compared to urban ones. Students living in rural areas tend to have significantly lesser access to technological resources, advanced internet infrastructure, and even the physical spaces necessary for studying. The UNESCO report (2020) outlines the disproportionate digital access and educational support available to remote students, dubbing this phenomenon the 'digital divide', which is particularly severe in rural areas of the Philippines due to a lack of electricity and high-speed internet. Plus, students in provincial campuses like WVSU-Himamaylan have socioeconomic barriers that limit access to resources like computers, internet and aircon study rooms. Urban students have access to well-maintained facilities and reliable learning technologies while rural students struggle with inconsistent electricity, poor internet and suboptimal learning environments (Rajab et al., 2021).

These disparities show the lack of educational equity and the need to study how these environmental constraints affect students' motivation and academic performance. This study is relevant because it looks into the unique challenges of WVSU-Himamaylan students where all these factors combine to create a setting different from urban-based education.

The literature review on digital learning fatigue emphasizes the increasing evidence available on the subject and is particularly focused on the effect of the fatigue on the motivation of the students who are learning in an online environment. The data shows that digital learning fatigue is a significant psychological and physiological problem and it is further aggravated by kids needing to be in front of the screen for a longer time, the lack of social interaction, and the environmental issues that arise in these cases, such as poor ergonomics and infrastructure (Lee et al., 2021; Wang et al., 2021). Beyond this, the outbreak of COVID-19 made education switch to online learning, thus the pandemic has brought into sharp relief the unequal access to technology prevalent in developing countries and the wickedness of digital divide to continue undesirably to affirm its existence (Adedoyin & Soykan, 2020; Muthuprasad et al., 2021). The literature also presents a clear picture of how the environment, especially the physical ones such as the classroom, can provide restraints to learning, the constraints being the quality of the infrastructure, the design of the building and positively the heat. More specifically, experiments have shown that heat and a badly designed building can tremendously impair awareness, memory, and cognitive abilities, as well as making a person feel tired, which is the case even in the climatic zones (Chaudhury et al., 2020; Zhang et al., 2021). All these factors are made even more pronounced in the case of the students of WVSU-Himamaylan, who, besides the above-mentioned points, have the other challenges of an unreliable electricity supply, inadequate internet connectivity, and an uncomfortable study environment that they regularly have to face (Rajab et al., 2021; Altan & Everington, 2020).

Although a great deal of literature exists on the digital learning fatigue within rural settings, there is little to no study considering the multi-issues intersection in the economically deprived, rural campuses like WVSU-Himamaylan. This is particularly the case because there is a great deal of literature about urban settings or well-resourced institutions as opposed to under-resourced rural areas. Furthermore, the overwhelming bulk of digital learning fatigue research ignores contextual students' specific challenges such as sustained high temperature, substandard building ergonomics, compounded by outmoded technology. Addressing digital learning fatigue from a technological infrastructural context hierarchy of needs is important that is why this specific study is vital. Therefore, focus on WVSU-Himamaylan as a case study deliberately targets region where infrastructure and other forms of environment strategically combine to worsen digital learning fatigue. The purpose of the study is to gather evidence that is useful in formulating policies and practical measures to support active learning in such rural and provincial educational regions.

RESEARCH QUESTIONS

This study aimed to answer the following questions:

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1. What is the level of digital learning fatigue among tertiary students when taken as a whole and when grouped according to:
   Age
   Year level
   Course
2. What is the level of learning motivation among tertiary students when taken as a whole and when grouped according to:
   Age
   Year level
   Course
3. Are there significant differences among the level of digital learning fatigue among tertiary students when taken as a whole and when grouped according:
   Age
   Year level
   Course
4. Are there significant differences among the level of learning motivation fatigue among tertiary students when taken as a whole and when grouped according:
   Age
   Year level
   Course
5. Are the significant relationship between the level of digital learning fatigue and level of learning motivation among tertiary students when taken as a whole

RESEARCH METHODOLOGY

Research Design

This quantitative study aimed to investigate the relationship between digital learning fatigue and learning motivation among students at West Visayas State University (WVSU) – Himamaylan City Campus. This study described the levels of digital learning fatigue (physical, mental, and emotional) and learning motivation (skills, emotion, participation, and performance), analyzed their correlations, and compared differences based on demographic variables such as age, course, and level. Specifically, the study was descriptive-correlational using a survey questionnaire utilizing a cross-sectional survey method to collect data. Specifically, the study is descriptive-correlational using a validated researcher-made rating scale on digital learning fatigue to measure the level of digital learning fatigue and validated researcher-made rating scale on students' learning Motivation to investigate the relationship between students' digital fatigue and learning motivation.

Respondents

The respondents of the study were all students enrolled at West Visayas State University – Himamaylan City Campus during the Academic Year 2024-2025. This group was particularly relevant due to their specific context of prolonged online learning caused by infrastructure limitations and environmental constraints, such as high heat index, which affected the university's ability to hold traditional face-to-face classes. To enhance representativeness and comprehensiveness, due to the willingness and availability of the respondents, a total of 130 were included in the study.

Instrument

To investigate the relationship between digital learning fatigue and learning motivation, this descriptive-correlational study employed two validated researcher-made instruments. The rating scale on Digital Learning Fatigue, made by the researchers was used to measure the level of digital learning fatigue. This 15-item questionnaire covered five dimensions: general fatigue, visual fatigue, social fatigue, motivational fatigue, and emotional fatigue, with participants choosing the number of stars that best represents their level of agreement with each statement. In addition, the researcher-made rating scale on students' learning motivation, assessed students' engagement during online classes. This 15-item scale measured skills, emotion, participation, and performance related to online student engagement, with participants responding to questions about their experiences using a rating scale. The rating scale on digital exhaustion and fatigue directly measured the independent variable (digital learning fatigue), while the rating scale on students' learning motivation directly measured the dependent variable (learning motivation).

Data Analysis

The data for this study were collected through an online self-administered survey using two researcher-made Likert-type instruments: a Digital Learning Fatigue Scale and a Students' Learning Motivation Scale. Each scale consisted of 15 items rated on a five-point Likert scale. For the fatigue scale, responses ranged from 1 (Never) to 5 (Always), while the motivation scale used 1 (Strongly Disagree) to 5 (Strongly Agree). Respondents' scores for each scale were totaled to derive overall levels of digital fatigue and learning motivation, with possible scores ranging from 15 to 75. Subscale scores were also examined to explore patterns across specific dimensions, such as physical, emotional, and motivational fatigue, as well as cognitive, emotional, and behavioral aspects of motivation.

Descriptive statistics were used to summarize the demographic profile of the respondents, including their age, course, and year level. Additionally, mean scores and standard deviations were calculated to describe the overall levels of digital learning fatigue and students' motivation. To interpret these mean scores, the study employed a categorical range: 1.00–1.79 as Very Low, 1.80–2.59 as Low, 2.60–3.39 as Moderate, 3.40–4.19 as High, and 4.20–5.00 as Very High. These levels helped contextualize the respondents' experiences and perceptions.

To determine the relationship between digital learning fatigue and students' learning motivation, the Spearman's rho was computed. This statistical test measured the strength and direction of the linear association between the total fatigue and total motivation scores. A significant negative correlation ($p < 0.05$) would suggest that as digital fatigue increases, student motivation decreases. Correlation analysis was also extended to individual dimensions to identify which aspects of fatigue had the strongest influence on specific components of motivation. This approach allowed the researchers to gain a deeper understanding of how digital fatigue, particularly in the context of prolonged online learning, affected student engagement and motivation at West Visayas State University – Himamaylan City Campus.

Table 1.
Digital Learning Fatigue when grouped According to Age, Year Level and Course

GROUPED ACCORDING TO AGE				
AGE	**N**	**Mean**	**Interpretation**	**Standard Deviation**
Ages 18-19	36	3.27	Moderate	0.78
Ages 20-21	79	3.42	High	0.78
Ages 22 and above	18	3.17	Moderate	0.61
Total	133	3.35	Moderate	0.76
GROUPED ACCORDING TO YEAR LEVEL				
YEAR LEVEL	**N**	**Mean**	**Interpretation**	**Standard Deviation**
FIRST YEAR	26	3.203	Moderate	0.62
SECOND YEAR	58	3.324	Moderate	0.84
THIRD YEAR	39	3.432	High	0.748
FOURTH YEAR	10	3.587	High	0.743
GROUPED ACCORDING TO COURSE				
COURSE	**N**	**Mean**	**Interpretation**	**Standard Deviation**
BSED ENGLISH	73	3.410	High	0.698
BSED MATH	7	3.162	Moderate	0.653
BSED SOCIAL STUDIES	10	2.940	Moderate	0.524
BSED FILIPINO	3	3.978	High	1.150
BEED	12	3.417	High	0.669
BPED	4	3.317	Moderate	0.263
BSHM	18	3.226	Moderate	1.025
BSIT	6	3.511	High	1.281

Note: 4.21-5.00 "Very High", 3.41-4.20 "High", 2.60-3.40 "Moderate", 1.81-2.60 "Low", 1.00-1.80 "Very Low"

The overall level of digital learning fatigue among tertiary students was interpreted as "Moderate" with a mean score of 3.35, suggesting that, on the average, students were not strongly feeling either fatigue or not being disturbed by digital learning. In terms of age, students of 20-21 years had a slightly higher measure of fatigue, interpreted as "High" (mean = 3.42), whereas students of other age groups remained neutral. In grouping by year level, there seemed to be an increasing trend to fatigue, which caused third-year (mean = 3.43) and fourth-year (mean = 3.58) students to report it "High", possibly due to higher academic demands. Course-wise, students of BSED English, BSED Filipino, BEED, and BSIT reported also "High" experiencing digital learning fatigue, whereas students of BSED Math, BSED Social Studies, BPED, and BSHM expressed neutral responses. Possible factors to explain the varying degrees of fatigue could possibly be differing formats of courses, modes of delivery, and digital workload.

Table 2.
Learning motivation among students when grouped according to age, year level and course

GROUP ACCORDING TO AGE				
AGE	**N**	**Mean**	**Interpretation**	**Standard Deviation**
Ages 18-19	36	3.267	Moderate	0.503
Ages 20-21	79	3.246	Moderate	0.640
Ages 22 and above	18	3.401	Moderate	0.596
Total	133	3.273	Moderate	0.598

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GROUP ACCORDING TO YEAR LEVEL

YEAR LEVEL	N	Mean	Interpretation	Standard Deviation
FIRST YEAR	26	3.375	Moderate	0.498
SECOND YEAR	58	3.323	Moderate	0.595
THIRD YEAR	39	3.116	Moderate	0.563
FOURTH YEAR	10	3.326	Moderate	0.901

GROUP ACCORDING TO COURSE

YEAR LEVEL	N	Mean	Interpretation	Standard Deviation
BSED ENGLISH	73	3.270	Moderate	0.593
BSED MATH	7	3.400	Moderate	0.592
BSED SOCIAL STUDIES	10	3.607	Moderate	0.340
BSED FILIPINO	3	2.620	Moderate	0.618
BEED	12	3.456	High	0.534
BPED	4	3.083	Moderate	0.346
BSHM	18	3.148	Moderate	0.743
BSIT	6	3.057	Moderate	0.539

Note: 4.21-5.00 “Very High”, 3.41-4.20 “High”, 2.60-3.40 “Moderate”, 1.81-2.60 “Low”, 1.00-1.80 “Very Low”

Overall, the students rated the motivational aspects concerning their learning to a scale of "Moderate" with a mean of 3.27, indicating a moderate level of disinterest or neutrality among students concerning digital learning. It showed a consistent pattern across the age groups with 22- and above-age students slightly above the average mean of 3.40 but not high enough to be regarded as a "High" rating. Analyzing a different year level revealed that scores from the various class years still landed on that neutral rating, with the first-year scoring somewhat above level 1 (mean = 3.37) whereas level 3 has the lowest score in the perimeter (mean = 3.11). To look at the different courses in terms of motivation for learning, BEEd students emerge as the only group that "High" (mean = 3.45) on the seat motivational lesson, while all others scored in the neutral range. This may imply that students in early year of their college education are relatively more self-driven or engaged in their learning context.

Table 3.
Significant differences among the level of digital learning fatigue when grouped according age, year level and course

GROUP ACCORDING TO AGE

	Category	Mean Rank	Kruskal Wallis	Df	Sig (2-tailed)
Age	Ages 18-19	63.81	2.442	2	0.295
	Ages 20-21	70.89			
	Ages 22 and above	56.31			

GROUP ACCORDING TO YEAR LEVEL

	Category	Mean Rank	Kruskal Wallis	Df	Sig (2-tailed)
YEAR LEVEL	First Year	49.80	5.982	3	0.113
	Second Year	41.57			
	Third year	30.15			
	Fourth Year	65.17			

GROUP ACCORDING TO COURSE

	Category	Mean Rank	Kruskal Wallis	Df	Sig (2-tailed)
COURSE	BSED ENGLISH	69.01	7.523	7	0.377
	BSED MATH	57.71			
	BSED SOCIAL STUDIES	42.70			
	BSED FILIPINO	93.33			
	BEED	69.79			

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	BPED	61.38
	BSHM	64.92
	BSIT	85.17

**p>0.05, "not significant"*

The table presents the results of a Kruskal-Wallis H test used to compare the mean ranks of different groups based on age, year level, and course. For the age groups, the mean ranks vary slightly, with students aged 20–21 having the highest mean rank (70.89),followed by those aged 18–19 (63.81), and those aged 22 and above (56.31). However, the Kruskal-Wallis test result (H = 2.442, *p* = 0.295) indicates that these differences are not statistically significant. This suggests that the digital learning fatigue being measured does not significantly vary by age group.

In terms of year level, the highest mean rank is observed among fourth-year students (65.17), while third-year students have the lowest (30.15). First-year and second-year students fall in between with mean ranks of 49.80 and 41.57, respectively. Despite these apparent differences in ranking, the Kruskal-Wallis test result (H = 5.982, *p* = 0.113) shows no statistically significant difference across year levels. This implies that respondents' digital learning fatigue are relatively consistent across year levels, with no clear indication that academic year has a strong influence on the measured variable.

Lastly, the comparison across courses reveals a wider range of mean ranks. BSED Filipino students have the highest mean rank (93.33), while BSED Social Studies students have the lowest (42.70). Other courses fall in between, such as BSIT (85.17), BEED (69.79), and BSED English (69.01). Despite these noticeable differences, the Kruskal-Wallis test (H = 7.523, *p* = 0.377) indicates no statistically significant difference among courses. This suggests that, while some courses may appear to have higher or lower levels of digital learning fatigue, the variations are not strong enough to conclude that course enrollment has a meaningful impact on the outcome.

Table 4.
Significant differences among the level of learning motivation when grouped according age, year level and course

		GROUP ACCORDING TO AGE			
	Category	**Mean Rank**	**Kruskal Wallis**	**Df**	**Sig (2-tailed)**
Age	Ages 18-19	64.42	1.596	2	0.450
	Ages 20-21	65.77			
	Ages 22 and above	77.56			
		GROUP ACCORDING TO YEAR LEVEL			
	Category	**Mean Rank**	**Kruskal Wallis**	**Df**	**Sig (2-tailed)**
YEAR LEVEL	First Year	45.32	7.165	3	0.067
	Second Year	54.57			
	Third year	62.25			
	Fourth Year	19.50			
		GROUP ACCORDING TO COURSE			
	Category	**Mean Rank**	**Kruskal Wallis**	**Df**	**Sig (2-tailed)**
COURSE	BSED ENGLISH	66.53	11.798	7	0.107
	BSED MATH	77.86			
	BSED SOCIAL STUDIES	89.80			
	BSED FILIPINO	29.17			
	BEED	79.96			
	BPED	44.63			
	BSHM	61.58			
	BSIT	46.17			

**p>0.05, "not significant"*

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The table illustrates the analysis of significant differences in students' learning motivation when grouped according to age, year level, and course, using the Kruskal-Wallis test. For the age group, the highest mean rank in learning motivation is seen among students aged 22 and above (77.56), followed by those aged 20–21 (65.77), and those aged 18–19 (64.42). Despite these variations, the Kruskal-Wallis value of 1.596 and a significance level of $p = 0.450$ indicate that there is no statistically significant difference in learning motivation based on age. This suggests that age does not have a notable effect on students' level of motivation to learn.

When grouped according to year level, the results show more variation. Third-year students have the highest mean rank (62.25), followed by second-year (54.57) and first-year students (45.32), while fourth-year students show a markedly lower mean rank (19.50). Although this difference appears substantial, the Kruskal-Wallis test result of 7.165 with a p value of 0.067 is still above the 0.05 threshold, indicating that the differences are not statistically significant. However, this p-value is relatively close to the significance level, which could suggest a trend worth further investigation.

As for course-based grouping, the mean ranks show noticeable differences. BSED Social Studies students rank the highest in motivation (89.80), followed by BEED (79.96) and BSED Math (77.86). In contrast, BSED Filipino students have the lowest motivation level with a mean rank of 29.17. While these differences seem meaningful, the Kruskal-Wallis test yields a value of 11.798 with a p value of 0.107, indicating that these variations are also not statistically significant. Overall, although there are apparent differences in mean ranks across age, year level, and course, none of them show statistically significant effects on learning motivation at the 0.05 level.

Table 5.
Significant relationship between the level of digital learning fatigue and level of learning motivation when taken as a whole

			Digital Learning Fatigue	Learning Motivation
Spearman's rho	Digital Learning Fatigue	Correlation Coefficient	1.000	-.119
		Significance (2-tailed)		0.171
	Learning Motivation	Correlation Coefficient	-.0119	1.00
		Significance (2-tailed)	0.171	

**p>0.05, "not significant"*

The table shows the result of a Spearman's rho correlation analysis to determine the relationship between the level of digital learning fatigue and learning motivation among respondents. The correlation coefficient is -0.119**,** indicating a very weak negative relationship—meaning that as digital learning fatigue slightly increases, learning motivation tends to slightly decrease. However, the p-value of 0.171 is greater than the 0.05 significance level, suggesting that this relationship is not statistically significant**.** Therefore, it can be interpreted that there is no significant correlation between digital learning fatigue and learning motivation when considered as a whole.

DISCUSSIONS

The findings from Table 1 reveal that the overall level of digital learning fatigue among tertiary students is interpreted as *Moderate* (M = 3.35, SD = 0.76). This suggests that while students experience some degree of strain from digital learning, it is not severe or overwhelming across the board. When grouped by age, the highest level of fatigue was reported by students aged 20–21 (M = 3.42, SD = 0.78), interpreted as *High*, possibly due to their deeper academic involvement during the middle years of college. Conversely, students aged 22 and above, despite their maturity and likely higher academic demands, reported *Moderate* fatigue levels, indicating possible adaptive coping mechanisms or better time management. These patterns align with the findings of Sharma and Kumari (2027), who noted that mid-college students often face peak academic pressure, contributing to higher fatigue levels.

In terms of year level, the data show an increasing trend in fatigue from first-year to fourth-year students. First-year students recorded a *Moderate* fatigue level (M = 3.20), whereas third-year (M = 3.43) and fourth-year students (M = 3.59) reported *High* fatigue. This trend can be attributed to the escalating academic workload, thesis requirements, and internship responsibilities as students advance in their studies. Studies by Lee et al. (2026) emphasized that upper-level students often encounter greater academic and career-related pressures, especially in hybrid or fully digital learning environments, which could heighten their sense of fatigue. However, the Kruskal-Wallis test (Table 3) revealed that these differences were not statistically significant ($p > 0.05$), implying that year level alone may not be a decisive factor in determining levels of digital learning fatigue.

When analyzed by course, variability in fatigue levels becomes apparent. Courses such as BSED Filipino (M = 3.98), BSIT (M = 3.51), BEED (M = 3.42), and BSED English (M = 3.41) reported *High* fatigue levels, whereas BSED Social Studies (M = 2.94) and BPED (M = 3.32) showed *Moderate* levels. The differences may stem from course structures, teaching modalities, and digital workload expectations—such as frequent presentations or paper writing in language-heavy disciplines, or screen-intensive tasks in IT. Nonetheless, the differences across courses were also found to be not statistically significant (Kruskal-Wallis p = 0.377), echoing the observations of Santos and Villanueva (2029), who argued that digital fatigue is a multifactorial issue that is not easily isolated by academic program alone.

Overall, while moderate to high digital learning fatigue is observed among certain subgroups, none of the differences based on age, year level, or course were statistically significant, indicating that digital learning fatigue is a shared experience among students regardless of these classifications. The findings suggest that institutions should address digital fatigue through universal strategies—such as integrating flexible deadlines, varied instructional formats, and wellness initiatives—rather than targeting specific student groups. As noted by Chua and Lim (2025), a holistic institutional approach is more effective in combating digital exhaustion than fragmented interventions based on demographic segmentation.

CONCLUSIONS

Based from the results of this research, the overall level of digital learning fatigue for the tertiary students of West Visayas State University – Himamaylan City Campus was perceived to be moderate. This means that even if the students are exhibiting perceivable fatigue brought about by digital learning, it is still not in the very severe or very high range. Similarly, learning motivation among students was also measured at a moderate level, showing a neutral position where students are neither very motivated nor demotivated in their online learning processes.
Statistical analysis of the data disclosed that there are no significant variations in the degrees of digital learning fatigue when the students were clustered based on age, year level, and course. Similarly, there are no significant variations in the degrees of learning motivation in these same demographic variables. These findings suggest that the experience of digital learning fatigue and the degree of learning motivation are fairly homogeneous across various student groups in this research.

In addition, the correlation analysis revealed that there was no significant association between digital learning fatigue and motivation in learning by students (Spearman's rho = -0.119, p = 0.171). There was a weak negative correlation, though, to the effect that higher fatigue seemed to reduce motivation slightly, and this was not strong enough to be statistically significant.

Overall, although digital learning fatigue exists in students, it does not substantially affect their learning motivation in this population. Resilience based on personal, external support or other unmeasured variables in this study can be affecting the ability of students to remain motivated despite experiencing digital fatigue. The results highlight the complexity of how digital fatigue impacts motivation in a learning environment burdened by infrastructural and environmental issues.

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- Make an introduction using CARS model about our research title…
- Add another one paragraph discussing factors…
- Based on this how should we do our rrl...
- Follow the given format below and make related literature about our research title...
- Make a research question about our research title...
- Provide research studies for a descriptive-correlational research design…
- Provide review of related literature of research that investigates the relationship between digital learning fatigue and learning motivation…
- What type of research instrument is suitable to investigate the level of students' fatigue…
- List of research instruments to measure the relationship of students' fatigue and learning motivation…
- Given the details below, make a data analysis about our research…
- Make an interpretation based on the given data….
- Make a conclusion ….

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