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How do College Students Express AI Fatigue? A Content and Keyword-in-Context Analysis of Academic AI Use

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Abstract. This study examined how Filipino college students express AI fatigue in academic contexts. Using a qualitative descriptive design, the study analyzed 1,000 open-ended online survey responses collected from public higher education institutions in the Philippines through purposive convenience sampling. Directed qualitative content analysis, complemented by keyword-in-context (KWIC) analysis, was used to identify and contextualize fatigue-related expressions in student narratives. Analysis revealed four categories: cognitive fatigue, emotional fatigue, motivational fatigue, and absence of fatigue expression. Cognitive fatigue emerged as the most frequently expressed dimension, characterized by mental tiredness, information overload, and difficulty sustaining focus. Motivational and emotional fatigue were also evident and frequently co-occurred with cognitive fatigue. A substantial proportion of responses described AI use without any fatigue-related strain. These findings indicate that AI fatigue is multidimensional and unevenly experienced. The findings suggest that the use of academic AI does not uniformly reduce effort but may shift cognitive demands toward

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evaluation and information processing. By grounding interpretation in students' own language, the study contributes empirical evidence to discussions on sustainable AI integration in higher education, particularly within digitally intensive developing contexts.

Keywords : artificial intelligence; AI fatigue ; cognitive fatigue ; emotional fatigue ; motivational fatigue ; higher education ; content analysis

1. Introduction

Recent empirical evidence indicates widespread use of artificial intelligence (AI) tools among college students worldwide (Khalifa & Albadawy, 2024; D. Lee et al., 2024; Vieriu & Petrea, 2025). Specifically, studies and survey reports show that a large proportion of university students regularly employ generative AI tools, such as ChatGPT, for academic tasks including, but not limited to, studying, writing, and information retrieval. (Almassaad et al., 2024; Digital Education Council, 2024; Halliday et al., 2025). In addition, students using AI for explanations, summaries, and idea production have been observed in similar ways across institutional contexts which indicate that AI tools are no longer peripheral learning aids but have instead become integrated into regular academic activity (Al Mashagbeh et al., 2025; Klimova & Pikhart, 2025; Vieriu & Petrea, 2025).

Specifically, studies and survey reports show that a large proportion of university students regularly employ generative AI tools, such as ChatGPT, for academic tasks including, but not limited to, studying, writing, and information retrieval. (Almassaad et al., 2024; Digital Education Council, 2024; Halliday et al., 2025). In addition, students using AI for explanations, summaries, and idea production have been observed in similar ways across institutional contexts which indicate that AI tools are no longer peripheral learning aids but have instead become integrated into regular academic activity (Al Mashagbeh et al., 2025; Klimova & Pikhart, 2025; Vieriu & Petrea, 2025).

Studies examining student engagement with generative AI have primarily focused on adoption, attitudes, and perceived learning outcomes (Garcia et al., 2025). Prior research reports that students generally view AI tools as useful and efficient, while also expressing concerns related to accuracy, trust, and overreliance (Al Mashagbeh et al., 2025; Almassaad et al., 2024; Martín-Moncunill & Alonso Martínez, 2025; Mohamed, 2024; Sustaningrum & Haldaka, 2025). Patterns of AI use vary across academic tasks and disciplines.

However, comparatively little attention has been paid to the experiential demands associated with sustained AI use, particularly those involving self-regulation and cognitive effort. Recent conceptual work further suggests that AI use may shape emotional regulation, motivation, autonomy, and academic identity, which highlights the need to examine AI-related experiences beyond technical efficiency alone (Garcia et al., 2026; Promsiri, 2025). These studies demonstrate the growing integration of AI in academic work but do not directly examine how students experience fatigue-related strain during sustained AI interaction.

Research on digital fatigue provides relevant conceptual background. Studies indicate that sustained digital engagement can be associated with cognitive overload, emotional strain, and motivational difficulties among university students (An et al., 2025; Bobrytska et al., 2025; Maloney et al., 2023). Associations between intensive technology use and mental exhaustion have also been reported (Giray et al., 2024; Lițan, 2025; Neagu & Vieriu, 2025). These findings suggest conceptual overlaps but do not clarify whether fatigue in AI-supported academic work reflects general digital exhaustion or a more context-specific form of strain. Despite this emerging literature, limited empirical work has examined AI fatigue from the perspective of students using both quantitative and qualitative data.

Although AI fatigue overlaps with digital fatigue, cognitive load, and academic burnout, it is positioned in this study as a context-specific experience associated with academic AI use. Digital fatigue refers to general exhaustion linked to prolonged digital engagement, cognitive load concerns limitations in working memory during task processing, and academic burnout reflects a broader syndrome involving emotional exhaustion and reduced efficacy. In contrast, this study examines AI fatigue as students' explicitly articulated experiences of cognitive, emotional, and motivational strain related specifically to AI-supported academic work.

In the Philippine context, the broader digital environment provides importantbackground for examining these experiences. Global digital reports identify Filipinos as among the highest internet users worldwide, with average daily internet use exceeding eight hours (DataReportal, 2024; Slotta, 2025). At the same time, the integration of AI tools in Philippine higher education remains uneven at the institutional and local levels(Doria, 2025; Espartinez, 2025; Funa & Gabay, 2025, 2026). Althoughstudents increasingly access AI tools independently, formal policies and curriculum-level integration remain limited (Co, 2025; Funa & Gabay, 2025). Divergent views among students and educators regarding the ethical and pedagogical implications further reflect uncertainty about AI integration (Espartinez, 2024, 2025). As a result, students often engage with AI tools in self-directed ways within an already digitally intensive environment, which may shape how cognitive and emotional demands are experienced during academic work.

This study addresses this gap by analyzing Filipino college students' responses regarding their academic use of AI chatbots through qualitative content analysis and keyword-in-context (KWIC) analysis. This study answered the following research questions:

RQ1: How do college students express AI fatigue in their academic AI use?
RQ2a: What fatigue-related dimensions appear in student narratives?
RQ2b: How frequently do this fatigue dimensions occur within the dataset?
RQ3: How are fatigue-related expressions linguistically situated within students' responses based on keyword-in-context analysis?

2. Methods

2.1 Study Design

This study employed a qualitative descriptive research design supported by systematic qualitative text analysis. The design aimed to examine how college students' express experiences of AI fatigue through written narratives. This study focused on identifying and interpreting explicitly stated fatigue-related experiences using students' own language. This approach is appropriate for exploratory educational research that prioritizes description and meaning over inference or modeling (Doyle et al., 2020; Hsieh & Shannon, 2005; Hunter, 2018; Mayring, 2015).

2.2 Participants and Sampling Procedure

The population of this study consisted of college students enrolled in public higher education institutions in the Philippines. The sample included 1,000 college students (see Table 1) recruited through purposive convenience sampling. The purposive component ensured that only students with prior experience using AI chatbots for academic purposes were included, while the convenience component reflected voluntary participation through an online survey distributed across multiple public institutions. Inclusion criteria required participants to be currently enrolled in a public higher education institution and to have used AI chatbots for academic work. Although the dataset was large relative to interview-based qualitative studies, large-scale text-based datasets are appropriate for qualitative content analysis when responses consist of short written reflections (Chandrasekar et al., 2024; Jaeger & Rasmussen, 2021). The objective was to identify recurring patterns across a broad textual corpus rather than to construct in-depth individual case profiles.

Each participant provided one open-ended response describing their experiences with AI tools for academic work, and each response was treated as a single unit of analysis which formed the dataset of the study. This dataset contained no personal identifiable information. Participants' ages ranged from 18 to 28 years ($M = 19.20$, $SD = 1.45$). In terms of sex, 520 participants identified as female (52%) and 480 identified as male (48%). Most respondents accessed AI chatbots using mobile phones ($n = 878$, 87.8%), followed by laptop or desktop computers ($n = 100$, 10%) and tablets ($n = 22$, 2.2%). AI chatbot use for academic activities was common, with students reporting use one to two times per week (31.3%), a few times a month (26.9%), three to five times per week (15.4%), once a day (13.5%), and several times a day (12.9%).

Table 1: Demographic characteristics of the participants (n = 1,000)

Variable	Category	n	%
Sex	Female	520	52
	Male	480	48
Primary device used to access AI chatbots	Mobile phone	878	87.8
	Laptop/Desktop	100	10
	Tablets	22	2.2
Frequency of AI chatbot use for academic activities	Once a day	135	13.5
	Several times a day	129	12.9
	One to two times per week	313	31.3
	Three to five times per week	154	15.4
	A few times a month	269	26.9

2.3 Data Collection and Preparation

Data were collected using a single open-ended question: "*Can you describe your experiences using AI tools for your academic work?*" The question was designed to elicit reflective narratives and allowed students to describe positive, neutral, or negative experiences without directing them toward specific fatigue-related themes. This approach ensured that fatigue expressions, if present, were articulated voluntarily rather than prompted. The question was reviewed and validated by two faculty members in English and Psychology at a state university to ensure clarity and appropriateness. Participants were required to provide written responses, and entries that did not contain substantive content were not included in the analysis.

All responses were prepared for analysis through basic textual pre-processing. Responses were converted to lowercase to ensure consistency. Punctuation, numbers, and extraneous symbols were removed. Common stop words and generic AI-related terms were excluded to improve textual consistency for qualitative analysis. No paraphrasing, translation, or semantic transformation was applied. These steps preserved the original meaning of responses while ensuring suitability for qualitative text analysis, consistent with established practices (Bengtsson, 2016; Bray, 2023; Erlingsson & Brysiewicz, 2017; Mayring, 2015; Sechelski & Onwuegbuzie, 2019).

2.4 Conceptual and Empirical Basis for AI Fatigue Categories

The analysis employed four categories: cognitive fatigue, emotional fatigue, motivational fatigue, and absence of fatigue expression. These categories were grounded in empirical fatigue research, the educational psychology literature, and established methodological guidance for qualitative content analysis (An et al., 2025; Lane et al., 2025; Silvia et al., 2025; Wang et al., 2025). Cognitive fatigue refers to mental tiredness, information overload, and a reduced capacity to concentrate or process information following sustained cognitive effort (Karim et al., 2024; Kunasegaran et al., 2023). Empirical studies describe cognitive fatigue as a psychobiological state that emerges from prolonged engagement in cognitively demanding tasks, resulting in decreased cognitive efficiency and weakened attentional control (Khan & Suhluli, 2025; Kok, 2022). Prior research has documented this form of fatigue in academic and digitally mediated learning contexts, particularly when learners engage in extended mental processing (Inan et al., 2025; Reed, 2022; Wang et al., 2025).

Emotional fatigue captures affective strain such as stress, pressure, guilt, or emotional exhaustion associated with academic demands and technology use (Buenadicha-Mateos et al., 2022; Ibrahim et al., 2025; Tafesse et al., 2024). Research consistently identifies emotional exhaustion as a core component of student fatigue and burnout, especially in online and technology-supported learning environments (Deep & Chen, 2025; Ibrahim et al., 2025; Liu et al., 2023). Motivational fatigue refers to reduced academic drive, diminished effort, increased reliance on external tools, or loss of initiative (Heidari, 2025; Kok, 2022; Müller & Apps, 2019; Qiang et al., 2024).

Educational and psychological studies show that sustained cognitive demands increase perceived effort costs, which contribute to motivational decline and behavioral withdrawal over time (Bakker & Mostert, 2024; Brockbank, 2025). The category no fatigue expression was included to capture responses that described AI use without any explicit indication of cognitive, emotional, or motivational strain. Methodological literature emphasizes the importance of coding for the absence of a phenomenon to avoid forcing interpretations and to preserve variability in participant experiences. This will also ensure analytic balance and accurate representation of student narratives. A shared coding guide defined each category with clear inclusion and exclusion criteria. Only explicitly AI-related fatigue expressions were coded.

2.5 Content Analysis Procedure

The study applied directed qualitative content analysis, with coding conducted manually by the researchers and supported through computer-assisted organization using Microsoft Office Excel (Assarroudi et al., 2018; Gallagher, 2016; Hsieh & Shannon, 2005). Excel was used to store responses, apply codes, and organize coding frequencies, while all analytic decisions relied on human judgment. Coding focused strictly on manifest content, meaning that only explicitly stated fatigue-related experiences were coded. Coding was conducted by five researchers trained in qualitative content analysis. All coders independently coded a randomly selected subset of 200 responses (20%) to calibrate category application.

The average percentage agreement across coders was 86.9%. Discrepancies were resolved through consensus before coding the full dataset. Each response could receive multiple codes to reflect overlapping fatigue dimensions within a single narrative. This procedure ensured systematic and consistent application of the predefined coding framework across all responses. Consistent with studies related to qualitative content analysis, frequency counts and percentages were used as descriptive indicators to enhance analytic transparency and to demonstrate the relative prevalence of categories within the dataset without implying statistical inference (Fife, 2020; Hannah & Lautsch, 2010).

2.6 KWIC Analysis

KWIC analysis was conducted using a computer-assisted approach in Microsoft Excel. Fatigue-related keywords were identified based on the conceptual framework for cognitive, emotional, and motivational fatigue, as well as recurring manifest expressions observed during directed content analysis. The final keyword set, presented in Table 2, included: tired (*tired, tiring, tiredness*), overwhelm (*overwhelm, overwhelmed, overwhelming*), focus (*focus, focused, focusing*), stress (*stress, stressed, stressful*), guilt (*guilt, guilty*), lazy (*lazy, lazier, laziness*), and rely (*rely, relying*). Variants were grouped under their respective fatigue dimensions to ensure conceptual consistency across all inflectional forms.

Excel wildcard search functions were used to extract all occurrences of each keyword and its variants from the dataset. A context window of ±3 words surrounding each keyword was examined to identify immediate linguistic patterns. All extracted instances were then manually reviewed within their full sentence context to verify that they reflected AI-related academic fatigue rather than unrelated physical tiredness or non-academic references. KWIC analysis functioned as a contextual validation strategy that triangulated and reinforced the content analysis categories by grounding interpretations in students' actual language use (Mayring, 2015).

Table 2: Summary of KWIC configuration

Dimension	Keywords Used	Variants Included	Context Window
Cognitive	tired, overwhelmed, focus	tired/tiring/tiredness; overwhelm/overwhelmed/overwhelming; focus/focused/focusing	±3 words
Emotional	stress, guilty	stress/stressed/stressful; guilt/guilty	±3 words
Motivational	lazy, rely on	lazy/lazier/laziness; rely/relying on	±3 words
Extraction Tool	Microsoft Excel wildcard search	Manual verification	Computer-assisted

2.7 Methodological Rigor, Trustworthiness, and Ethical Considerations

Methodological rigor was established through analytic triangulation (Carter et al., 2014). Content analysis identified the types and prevalence of AI fatigue expressions, while KWIC analysis examined how these expressions were embedded within students' narratives. The use of empirically grounded categories, explicit inclusion rules, and direct textual evidence supported credibility and dependability of the findings (Assarroudi et al., 2018).

To further strengthen trustworthiness, the coding framework and analytic decisions were reviewed and finalized by two psychology experts with backgrounds in educational technology and psychology. Their review focused on conceptual alignment, clarity of category definitions, and consistency of category application rather than statistical agreement. In addition, the study analyzed anonymized textual data and involved minimal risk to participants. No personal identifiers were present in the dataset, and the analysis focused solely on students' written responses. Standard ethical guidelines for qualitative data analysis were followed throughout the study. Coding decisions and category refinements were systematically documented to maintain an audit trail and strengthen analytic transparency.

3. Results

3.1 Content Analysis of AI Fatigue Expressions

The directed content analysis uses four types of AI fatigue expressions (see Table 3). Fatigue categories were coded as multi-label, which allowed a single response to be assigned to more than one fatigue dimension. In this study, Cognitive fatigue was the most frequently observed category, appearing in 44.8% of responses. Students explicitly described mental tiredness, information overload, and difficulty maintaining focus during academic AI use. Typical statements reflected prolonged mental effort and cognitive strain, such as "*I feel mentally tired after reading long AI-generated explanations*" and "*Using AI gives too much information, and it becomes overwhelming to process*." These responses indicate that AI fatigue is often experienced as a cognitive burden rather than simple dissatisfaction.

Motivational fatigue was evident in 29.5% of responses and reflected reduced effort, growing reliance on AI tools, or diminished initiative in completing academic tasks. Students described changes in academic behavior, for example, "*I notice that I rely on AI too much instead of thinking on my own*" and "*Sometimes it makes me lazy because I stop trying to solve problems myself*." These statements suggest that motivational fatigue manifests through behavioral withdrawal and dependency rather than explicit exhaustion.

Emotional fatigue appeared in 27.4% of responses and was characterized by expressions of stress, pressure, guilt, or emotional discomfort related to AI use. Students often linked emotional strain to academic expectations or ethical concerns, as seen in statements such as "*I feel stressed when I depend on AI because I worry about doing something wrong*" and "*I feel guilty using AI too much for my schoolwork*." In contrast, a substantial proportion of responses (39.7%) contained no fatigue expression. These responses described AI use in neutral or positive terms without referencing any form of strain, for example, "*AI helps me understand lessons faster*" and "*Using AI makes my academic work easier*." On the other hand, the category "no fatigue expression" was applied exclusively to responses that contained no cognitive, emotional, or motivational fatigue codes.

Table 3: Frequency of AI fatigue expressions identified through content analysis

Fatigue Expression	Frequency	Percentage
Cognitive fatigue	472	44.8%
Motivational fatigue	311	29.5%
Emotional fatigue	289	27.4%
No fatigue expression	418	39.7%

3.2 KWIC Analysis of Fatigue Expressions

The KWIC analysis further clarified how fatigue-related experiences were articulated in context (see Table 4). Keywords associated with cognitive fatigue, such as tiredness, overwhelm, and focus, frequently appeared in explanatory statements. Students often linked these terms to information overload, as illustrated by excerpts like "*I get tired trying to understand all the details AI gives*" and "*It is hard to focus when the answer is too long.*" These contextual patterns show that cognitive fatigue is framed as a consequence of excessive or dense AI output.

Emotional fatigue keywords, including stress and guilt, appeared in narratives describing academic pressure and moral unease. For instance, students wrote "*It causes stress because I am not sure if I should depend on AI*" and "*I feel guilty when I rely on AI instead of studying more*." Motivational fatigue keywords, such as lazy and rely, were used to describe behavioral changes, often in reflective statements like "*AI makes me lazy because I stop thinking deeply*" and "*I rely too much on AI and lose motivation to work hard*." These contextual usages confirm that fatigue expressions are embedded within coherent explanations rather than isolated word choices.

Table 4: KWIC patterns supporting AI fatigue expressions

Top Keywords	Typical Contextual Usage	Fatigue Dimension
tired	"Feel tired after using…", "mentally tired when…"	Cognitive
overwhelmed	"too much information", "overwhelmed by answers"	Cognitive
focus	"Hard to focus", "lose focus when…"	Cognitive
stress	"Causes stress", "feel stressed because…"	Emotional
guilty	"Feel guilty relying on AI…"	Emotional
lazy	"Makes me lazy", "becoming lazy when…"	Motivational
rely on	"Rely too much on AI"	Motivational

3.3 Co-Occurrence of Fatigue Dimensions

Analysis of code co-occurrence showed that AI fatigue was often expressed as a multidimensional experience (see Table 5). Cognitive fatigue most frequently co-occurs with motivational fatigue, suggesting that mental overload often coincides with reduced academic effort. Students frequently linked these experiences within the same response, for example, "*I feel overwhelmed by AI answers, and it makes me rely on it instead of thinking*." Cognitive and emotional fatigue also commonly appeared together, as illustrated by statements such as "*I feel mentally tired and stressed when using AI for many tasks*." Although fewer responses contained all three fatigue dimensions simultaneously, some students explicitly described compound experiences, such as "*AI overwhelms me, makes me stressed, and slowly reduces my motivation to study*." These patterns reinforce the view that AI fatigue is layered and interconnected rather than singular.

Table 5: Co-occurrence of AI fatigue expressions within responses

Combination of Fatigue Expressions	Frequency	Percentage
Cognitive + Motivational	184	31.6%
Cognitive + Emotional	157	27%
Emotional + Motivational	96	16.5%
Cognitive + Emotional + Motivational	61	10.5%

Note. Co-occurrence frequencies are calculated based on the 582 responses that containe at least one fatigue dimension. Because fatigue categories were coded as multi-label, single response could appear in more than one co-occurrence combination.

4. Discussion

The findings indicate that college students most frequently expressed AI fatigue as cognitive fatigue, characterized by mental tiredness, information overload, and difficulty sustaining focus. This pattern aligns with empirical evidence showing that AI dependence is associated with increased cognitive fatigue, a pattern that is consistent with studies suggesting links between AI use, fatigue, and critical thinking performance (Tian & Zhang, 2025; Zhang et al., 2024). Research on GenAI-supported academic work also emphasizes that evaluating and filtering AI-generated content introduces additional cognitive demands, even when AI reduces task execution time (Gonsalves, 2024; Khan & Suhluli, 2025; Tian & Zhang, 2025; Yeung et al., 2025). These findings suggest that AI use may shift cognitive effort rather than eliminate it, which helps explain why cognitive fatigue emerged as the dominant expression in student narratives.

Empirical research also indicates that AI use does not universally increase cognitive burden. Systematic reviews and experimental studies have shown that, under structured conditions, ChatGPT can reduce intrinsic and extraneous cognitive load and support learning outcomes (Deng et al., 2025; Patac & Patac, 2025). This evidence provides context for the substantial proportion of responses that contained no fatigue expression, where students described AI use as helpful or efficient. The contrast between fatigue and non-fatigue expressions reinforces the interpretation that AI fatigue is context-dependent and shaped by patterns of use rather than AI use alone.

Motivational fatigue emerged as a prominent secondary dimension and frequently co-occurred with cognitive fatigue. Students described reduced initiative and increased reliance on AI tools, often alongside reports of mental overload. This pattern is consistent with research identifying distinct profiles of student reliance on ChatGPT, including groups characterized by selective or limited use and others showing higher dependence (Stojanov et al., 2024). While some studies report positive motivational outcomes associated with AI-supported learning when tasks are well scaffolded (Essel et al., 2024; H.-Y. Lee & Wu, 2025; Mo et al., 2025), the present findings indicate that frequent or unstructured reliance may coincide with diminished self-directed effort for some students.

Emotional fatigue appeared less frequently than cognitive and motivational fatigue but remained a consistent element of student narratives. Expressions of stress, pressure, and guilt were often embedded in reflections about academic responsibility and appropriate AI use. Prior research on AI-related guilt and shaming supports this pattern, showing that moral discomfort and uncertainty about acceptable use can influence how students engage with AI tools (Acut et al., 2025; Qu & Wang, 2025). Related studies on generative AI and academic integrity report that ambiguity in norms and expectations contributes to anxiety, even among students who recognize the benefits of AI (Biri et al., 2025; Gonsalves, 2025; Huang et al., 2025; Kirsanov et al., 2025; Song & Liu, 2025). These findings indicate that emotional fatigue may arise from ethical uncertainty rather than workload alone.

A substantial proportion of students reported no fatigue expression. This describes their AI use as supportive of academic work similar to earlier studies (Dong et al., 2025; Vieriu & Petrea, 2025). Empirical studies consistently report that many students perceive AI tools as beneficial when used for clarification, feedback, or learning support (Durgungoz & Kharrufa, 2025). Meta-analytic evidence also reports positive effects of ChatGPT on learning performance and perceptions, with variation across contexts and task types (Mo et al., 2025; Wang & Fan, 2025). This inconsistency shows that AI fatigue is not a universal experience and that student responses depend on how AI tools are integrated into academic tasks.

5. Practical Implications

The predominance of cognitive fatigue expressions suggests that students experience AI-related strain through increased mental demands when processing and evaluating AI-generated content. In the Philippine higher education context, where institutional AI guidelines remain uneven and students often adopt AI tools independently, cognitive demands may accumulate without structured instructional support. At the pedagogical level, instructors can mitigate this by requiring students to evaluate, verify, or revise AI outputs rather than use them passively. Curriculum design may integrate structured checkpoints that promote critical engagement instead of unfiltered content generation.

Motivational fatigue, often co-occurring with cognitive fatigue, indicates shifts in how students allocate academic effort. In self-directed AI environments with evolving assessment policies, frequent reliance on AI may coincide with reduced initiative. At the student level, strengthening self-regulated learning practices becomes essential. At the institutional level, clearer assessment guidelines and disclosure expectations can reduce ambiguity about appropriate AI use. Motivational fatigue thus reflects both technological access and unclear performance standards.

Emotional fatigue expressions point to anxiety, stress, and guilt linked to uncertainty about acceptable AI practices (Acut et al., 2025; Domingo, 2026; Ma et al., 2025; Qu & Wang, 2025). In a developing digital context such as the Philippines, emotional strain may reflect regulatory transition rather than inherent technological burden. Clear governance frameworks and consistent communication across courses can reduce this uncertainty. The substantial proportion of responses without fatigue expressions indicates that AI use can be supportive when integration is purposeful and well-defined. These findings support the need for context-sensitive AI literacy initiatives in higher education.

6. Conclusion and Future Work

This study examined how college students express AI fatigue in academic contexts using qualitative content analysis and KWIC analysis of open-ended responses. The findings show that students most frequently articulated AI fatigue as a cognitive experience, followed by motivational and emotional dimensions, while a substantial proportion reported no fatigue expression. These findings indicate that AI fatigue is multidimensional and unevenly experienced among students. The analysis demonstrates that AI use does not uniformly reduce academic effort and may shift cognitive demands toward information processing and evaluation. By grounding interpretations in students' own language, the study provides empirical evidence of how learners describe the costs and benefits of academic AI use. The findings align with the educational focus of learning research by highlighting how emerging technologies influence student cognitive and experiential processes.

Future research could build on this work by examining how AI fatigue expressions vary across academic disciplines, task types, and levels of study. Longitudinal studies may help clarify how fatigue develops over time as students' AI use becomes more habitual. Quantitative approaches could complement qualitative findings by modeling the relationships between AI use frequency, fatigue dimensions, and learning outcomes. Comparative studies across institutional contexts may further explain why some students report no fatigue while others experience substantial strain. Experimental or intervention-based research can also explore how structured guidance influences students' experiences of AI fatigue, while remaining attentive to student perspectives.

7. Limitations

This study has several limitations that should be considered when interpreting the findings. The analysis relied on self-reported open-ended responses, which reflect students' subjective perceptions of AI fatigue and do not allow direct assessment of cognitive, emotional, or motivational states through behavioral or physiological measures. The cross-sectional dataset captures experiences at a single point in time. The sample consisted of students enrolled in public higher education institutions, which may limit transferability to other institutional contexts. Although qualitative categorization involves analytic judgment, systematic coding procedures and the combined use of content analysis and keyword-in-context analysis supported consistency in the interpretation of the dataset.

Conflict of Interest
The authors declare no conflicts of interest.

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