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AI-induced fatigue among students in higher education: a latent profile analysis

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ABSTRACT

The integration of artificial intelligence (AI) tools in education offers significant benefits but also introduces challenges, including AI-induced fatigue among students. This study aimed to classify students' experiences with AI tools using latent profile analysis (LPA). A quantitative cross-sectional design and referral approach were used to collect survey data from 388 college students who actively used AI tools for academic purposes from November to December 2024. The survey measured AI usage intensity, AI literacy, self-efficacy, perceived usefulness, cognitive load, technostress, sleep quality, general fatigue levels, and attitude toward AI. Descriptive results indicated moderate levels of AI usage intensity, AI literacy, perceived usefulness, cognitive load, sleep quality, and general fatigue, with technostress and attitude toward AI also at moderate levels. Model selection considered Akaike information criterion (AIC), Bayesian information criterion (BIC), entropy, and profile size adequacy, and expert review supported the retained six-profile structure. The LPA identified six interpretable user groups: competent but sleep-deprived users, overwhelmed and high-strain users, stable moderate users, strained moderate users, high-intensity strained users, and low-strain selective users. The findings show differences in patterns of competence, strain, fatigue, and sleep outcomes associated with AI tool use, which supports the development of profile-specific strategies to manage technostress, cognitive load, fatigue, and sleep disruption among higher education students.

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1. INTRODUCTION

Artificial intelligence (AI) tools now support writing, problem solving, feedback generation, and productivity tasks in higher education settings [1], [2]. Universities increasingly expect students to demonstrate AI literacy, prompt formulation skills, and critical judgment when interacting with these systems [2]. Educators report gains in efficiency and instructional support. Despite these, they also encounter challenges related to training, curriculum redesign, and changes in student-teacher interaction [3]. Beyond these implementation concerns, intensive AI use introduces a student-centered outcome that remains underexamined in empirical research, which few scholars describe it as AI-induced fatigue [4]. This condition refers to sustained cognitive strain and emotional exhaustion that emerge from repeated evaluation, verification, and adaptation to AI-generated outputs. Empirical reviews of AI use in higher education report early signs of digital fatigue and well-being concerns among students, which highlight the presence of AI-specific stressors that require focused investigation [5].

Studies on generative AI adoption in educational contexts further identify psychological stress linked to continuous AI interaction and information overload which emphasize the relevance of AI-induced fatigue as a distinct construct [6]–[8]. Although related research connects these outcomes to technostress and cognitive strain in digital environments, existing studies rarely isolate AI-specific mechanisms within academic contexts [8]–[11]. Studies on student well-being present mixed evidence on the consequences of AI use. Research shows that AI systems can enhance learning through personalization, rapid feedback, and collaborative affordances that support academic engagement [2], [12]. Students often report higher productivity and improved language support when they rely on AI tools for coursework [13]. At the same time, scholars associate excessive dependence on AI with burnout symptoms, reduced self-regulation, and declines in psychological well-being [14], [15]. These studies suggest that benefits and risks coexist rather than follow a single trajectory. Current literature, however, tends to treat students as a homogeneous group, which limits understanding of how different patterns of AI use relate to fatigue outcomes.

Research in the Philippine higher education context shows rapid student adoption of AI tools, particularly for writing and academic support tasks [16]. Empirical evidence points to uneven levels of awareness, confidence, and use across age groups, academic years, and disciplines [17]. Such variation implies that students encounter AI-related demands in different ways, yet local studies rarely examine these differences systematically. Most existing work relies on descriptive comparisons or general attitude measures rather than person-centered approaches. As a result, the literature provides limited guidance for identifying which students face higher risks of AI-related strain. This gap constrains the design of targeted institutional responses in developing higher education systems.

This study addresses this gap through latent profile analysis (LPA) that examines AI-induced fatigue among higher education students in the Philippine context. Existing research emphasizes the instructional and productivity benefits of AI. Despite these, there are limited evidence on how students experience AI use in varied and uneven ways. This study identifies distinct student profiles based on AI literacy, self-efficacy, technostress, cognitive load, and fatigue levels. The person-centered approach moves the analysis away from average effects and toward structured patterns that represent meaningful subgroups of AI users. The study connects these profiles with differences in AI usage intensity and academic demands to explain how fatigue manifests across conditions which may provide empirical grounding for potential targeted interventions to properly support sustainable and balanced AI use in higher education.

2. METHOD

This study employed a quantitative, cross-sectional design to identify latent profiles of college students based on their experiences with AI-induced fatigue and to examine the factors influencing these profiles. Respondents were required to meet the following inclusion criteria: they must be actively enrolled in a college or university in the Philippines and have experience using AI tools for academic purposes. Students who did not use AI tools in their academic work were excluded from the study. The survey instrument consisted of 36 items, with 31 items adapted from existing validated studies (Table 1). The instrument measured constructs related to AI usage intensity, AI literacy, self-efficacy, perceived usefulness, cognitive load, sleep quality, general fatigue levels, technostress, and attitude toward AI. To ensure clarity and reliability, the instrument was pilot-tested with 30 students before full implementation. The final survey was distributed via Google Forms, using student group chats on Messenger for dissemination. Data collection occurred from November to December 2024. The study used referral approach to identify potential respondents for the study. Initially, students in a university were asked to answer the survey and forward the Google Form link to their classmates or friends from within and outside their university who are using AI tools. Ethical considerations adhered to the principles outlined in the Philippine Data Privacy Act and the guidelines for the conduct and reporting of survey research.

The data collected from the final survey were analyzed using Python and its associated libraries. Pandas was used for data cleaning, preprocessing, and aggregation of multi-item constructs into composite scores. It was also used for the descriptive statistics (e.g., means and standard deviations) were used to summarize demographic information and key variables. Scikit-learn was utilized to perform standardization of data and conduct LPA using gaussian mixture models. LPA is a person-centered approach used to identify subgroups within populations based on shared characteristics. In educational settings, LPA has been applied to study burnout, engagement, and quality of life among students [18]–[20]. LPA has also been used to examine the relationship between time perspective, burnout, and depression in adolescents [21], as well as health-related quality of life, sleep quality, and internet addiction among medical students [22]. Model selection considered fit statistics (Akaike information criterion (AIC) and Bayesian information criterion (BIC)), classification quality (entropy), profile size adequacy, and expert review of competing structure of information criteria across different model specifications was performed using Python in Jupyter Notebook environment. The results of the LPA were interpreted to identify distinct student profiles characterized by varying levels of AI literacy, self-efficacy, technostress, cognitive load, fatigue, and attitudes toward AI. After selecting the final LPA structure, inferential comparisons were conducted across profiles. Chi-square tests of independence were applied to examine whether categorical variables (e.g., sex) differed significantly across latent profiles. One-way analysis of variance (ANOVA) was used to compare mean differences in continuous construct scores across profiles.

Table 1. Operational definitions, measurement scales, and sources of constructs in the instrument

Construct	Definition	Items	Measurement	Source
AI usage intensity	The frequency and duration of AI tool usage for academic purposes.	2	Likert scale and ratio	Custom-developed
AI literacy	The degree of understanding, effective use, and awareness of the limitations of AI tools.	3	Likert scale	[23], [24]
Technostress	The stress and overwhelm caused by using AI tools, including difficulty adapting to or managing their complexities.	3	Likert scale	[8], [25]
Self-efficacy in AI use	The confidence in one's ability to effectively use AI tools for academic tasks.	2	Likert scale	[26], [27]
Perceived usefulness of AI	The extent to which AI tools are believed to improve academic performance and efficiency.	3	Likert scale	[28], [29]
Cognitive load	The mental effort required to use AI tools effectively for learning.	3	Likert scale	[30], [31]
Sleep quality	The impact of AI-related academic tasks on students' ability to sleep well and feel rested.	2	Likert scale	[32]–[34]
General fatigue levels	The overall physical and mental exhaustion experienced from prolonged or frequent AI use.	3	Likert scale	[35], [36]
Attitude toward AI	The degree of positivity or negativity in students' perceptions of AI tools and their potential.	3	Likert scale	[37], [38]

2.1. Demographic profile of the respondents

There 388 respondents in this study. All are students from universities in Central Luzon, Philippines. They 60.6% are female and 39.4% are male. The age ranged of the respondents were 17 to 35 years old. The respondents majored in education and teacher training (28.4%), tourism and hospitality management (23.2%), computer science and information technology (20.6%), engineering and technology (18%), humanities and social sciences (7.5%), business and management (1.8%), and mathematics and natural sciences (0.5%). More than half or the respondents are third year (55.4%). This was followed by first year (36.1%), fourth year (6.4%), and second year (2.1%). The 33.8% of the respondents stated that they always have access to a laptop or computer for their academic use. In terms of their use of AI tools for academic purposes, 50.5% of the respondents indicated that they sometimes use them. Only 5.9% and 17.5% mentioned they use them often and always respectively. These respondents are using AI tools for their studies from one up to 60 hours times a week. On average they are using AI tools three hours per week. The 49% of them stated that they are using AI tools at least for an hour a week. The 25.3% of them are dedicating one hour of their week for academic tasks outside class hours. The average hours dedicated by the respondents to academic tasks outside class hours is seven hours. The 10.1% of the respondents reported dedicating 20 or more hours outside class hours. One respondent reported allocating 100 hours for academic tasks outside classes alone.

3. RESULTS AND DISCUSSION

3.1. Descriptive statistics

Table 2 shows that students use AI tools moderately use AI tools in their education (mean =2.960, standard deviation (SD) =0.947). On average, students reported having a moderate to slightly higher level of AI literacy (mean =3.472, SD =0.953). Students indicated that AI use does not overwhelm them (mean =2.638, SD =0.614). In terms of self-efficacy, students are moderately confident and capable in their ability to use AI tools effectively. In terms of cognitive load, students indicated that they exert moderate effort in using AI tools (mean =2.814, SD =0.761). For sleep quality, students reported having moderate sleep disturbances likely due to AI-related use (mean =2.785, SD =0.585). This also true for their reported fatigue levels (mean =2.699, SD =0.858). For attitude, students have neutral to slightly positive attitudes towards AI tools (mean =2.883, SD =0.479).

Table 2. Descriptive statistics of AI use and student well-being variables

Construct	Mean	SD
AI usage intensity	2.960	0.947
AI literacy	3.472	0.953
Technostress	2.638	0.614
Self-efficacy in AI use	3.182	0.786
Perceived usefulness of AI	3.371	0.868
Cognitive load	2.814	0.761
Sleep quality	2.785	0.585
General fatigue levels	2.699	0.858
Attitude toward AI	2.883	0.479

3.2. Latent profile analysis

The LPA identified six distinct profiles of college students based on AI literacy, self-efficacy, perceived usefulness, cognitive load, sleep quality, general fatigue, technostress, attitude toward AI, and AI usage intensity. Two to ten profiles were evaluated using AIC, BIC, entropy, and profile size adequacy (Table 3). Although more profiles yielded lower fit indices, these models produced class fragmentation and several very small profiles, which suggests overextraction and reduced interpretability. The eight-profile structure yielded the lowest BIC, but it generated four profiles below the 5%, including an extremely small class, which raised concerns regarding stability. In contrast, the six-profile structure maintained strong classification quality and produced only one profile slightly under the 5%. Two expert validators (professors of educational technology and psychology in a state university) reviewed the competing structures from k =3 to k =8 and agreed that the six-profile structure provided the clearest conceptual differentiation and the most actionable interpretation for intervention-oriented analysis, particularly because k =7 and k =8 showed evidence of fragmentation despite improved fit indices.

Table 3. Model fit indices for competing latent profile structure

Profiles (k)	AIC	BIC	Entropy	Min_Class_%	# Profiles <5%
2	5988.51	6420.26	0.9993	31.44	0
3	4718.87	5368.48	0.8514	21.65	0
4	4977.42	5844.88	0.8979	2.32	1
5	4098.13	5183.44	0.9849	2.84	1
6	3965.14	5268.31	0.9768	3.61	1
7	3870.82	5391.85	0.9786	1.80	3
8	2934.71	4673.59	0.9543	0.77	4
9	3326.84	5283.58	0.9844	0.77	5
10	2754.69	4929.28	0.9714	2.06	6

Table 4 summarizes the profile labels and key characteristics, and class sizes further supported the interpretability of the retained structure. Profile sizes were uneven but acceptable for interpretation. Profile 5 was the largest class (n =145), followed by profile 6 (n =83) and profile 3 (n =70). Profile 1 included 51 respondents, profile 2 included 25 respondents, and profile 4 was the smallest class (n =14). The presence of one small class was considered acceptable because it reflected a coherent pattern in the profile means and did not indicate widespread instability, unlike the higher-k structures shown in Table 3. The six-profile structure also aligned with the profile adequacy criteria used in person-centered analysis, where interpretability and stability are prioritized alongside statistical fit.

Profile interpretation showed clear differences across competence-related and strain-related dimensions. Profile 1 included high-competence users with relatively high AI literacy and self-efficacy, low technostress and cognitive load, but poor sleep quality and moderate fatigue. Profile 2 represented overwhelmed users with very low AI literacy, self-efficacy, and perceived usefulness, combined with high cognitive load, high technostress, poor sleep quality, and high fatigue. Profile 3 reflected moderate and stable users with average competence and manageable technostress and fatigue. Profile 4 represented a small but distinct subgroup characterized by elevated strain and persistent fatigue and sleep issues. Profile 5 captured high-intensity users who reported high AI usage intensity, high competence, and high perceived usefulness, but also high technostress, high cognitive load, poor sleep quality, and high fatigue. Profile 6 consisted of low-stress moderate users with lower competence levels but low technostress and cognitive load and stable sleep quality and fatigue levels.

Table 4. Distinct profiles

Profile	n	Label	Key characteristics
1	51	Competent but sleep-deprived users	High competence, low strain, poor sleep, and moderate fatigue
2	25	Overwhelmed and high-strain users	Low competence, high technostress and cognitive load, poor sleep, and high fatigue
3	70	Stable moderate users	Moderate competence, manageable technostress, and average sleep and fatigue
4	14	Strained moderate users	Moderate competence, elevated strain, persistent fatigue, and sleep issues
5	145	High-intensity strained users	High usage, high competence, high strain, poor sleep, and high fatigue
6	83	Low-strain selective users	Low-to-moderate competence, low strain, and stable sleep and fatigue

3.3. Differences in LPA profiles and their descriptive statistics

The chi-square test showed no statistically significant association between sex and latent profile membership, $\chi^2(5)$ =10.48, p =063, with a small effect size (Cramér's V =16) which indicates a limited differences in the distribution of male and female respondents across profiles. This result suggests that profile membership did not substantially vary by sex in the present sample. On the other hand, ANOVA showed statistically significant differences across profiles for sleep quality, technostress, AI literacy, perceived usefulness, AI usage intensity, general fatigue, cognitive load, and self-efficacy (all p <.001). Sleep quality showed the strongest profile separation, F(5, 382) =44.69, p <.001, with poorer sleep observed in the high-strain profiles (particularly profiles 2 and 5) and more stable sleep outcomes in profile 6. Technostress also differed significantly across profiles, F(5, 382) =27.05, p <.001, with the highest levels concentrated in profiles 2 and 5 and comparatively lower levels in profiles 1 and 6. Competence-related constructs also varied significantly, including AI literacy, F(5, 382) =12.91, p <.001, and self-efficacy, F(5, 382) =4.24, p <001, where profile 2 reflected the lowest competence and profiles 1 and 5 reflected higher competence patterns. In contrast, attitude toward AI did not significantly differ across profiles, F(5, 382) =2, p =.078 which shows a relatively similar attitudes toward AI despite differences in fatigue-related outcomes.

4. CONCLUSION

This study demonstrates that students' experiences with AI tools vary significantly. They cover distinct profiles that range from low-stress, balanced users to high-intensity, fatigued individuals. These results show the importance of tailored interventions to address specific challenges such as low AI literacy, technostress, and sleep disruptions. For instance, students under profile 1 require support in improving time management and minimizing AI-related sleep disruptions, while profile 2 students benefit from foundational AI literacy training to build confidence and reduce technostress. Simplified tools and enhanced user support can further ease their cognitive load. For profile 3, periodic support and resources are sufficient to maintain their balanced usage and prevent burnout, as minimal intervention is otherwise needed. Likewise, students in profile 4 may gain from stress management techniques and strategies to improve sleep quality, alongside optimized AI tools to lower cognitive load. Similarly, interventions for profile 5 should focus on reducing technostress and cognitive load through user-friendly tool design, while encouraging breaks and better sleep habits to alleviate fatigue. For profile 6, opportunities to enhance AI literacy and self-efficacy can help them maximize the benefits of AI tools, although their low stress levels indicate that minimal additional support is necessary. Through LPA, the study was able to highlight the potential for profile-specific interventions to address students' unique needs related to AI-induced fatigue. Institutions can not only improve academic outcomes based on these results but also foster positive and empower experiences with emerging technologies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there are no known conflicts of interest associated with this publication. There are no financial or personal relationships that could inappropriately influence or bias the content of this work.

INFORMED CONSENT

We obtained informed consent from all study participants in strict accordance with institutional ethical guidelines and the Declaration of Helsinki; participants were comprehensively informed about the study's objectives, detailed procedures, potential risks and benefits, data confidentiality and handling practices, as well as their unconditional right to withdraw participation at any time without any penalty or prejudice, and all signed consent forms were securely stored to uphold compliance, confidentiality, and participant privacy.

ETHICAL APPROVAL

This research adhered to ethical guidelines including the Belmont Report, Helsinki Declaration, Philippine Data Privacy Act of 2012, and PCHRD's 2022 guidelines.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [JPPM], upon reasonable request.

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