



RESEARCH ARTICLE

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TEXT MINING ANALYSIS OF STUDENTS' EXPERIENCES AND FATIGUE TOWARDS FREQUENT AI TOOL USE IN ACADEMIC WORK

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ABSTRACT

The growing use of artificial intelligence (AI) tools among college students has raised concerns about their psychological and behavioral consequences, particularly in relation to academic fatigue and dependence. However, student-reported experiences with frequent AI tool use remain underexplored in the text mining literature. This study analyzed the open-ended survey responses of 491 college students using text mining methods to determine their experiences and fatigue toward frequent AI tool use in academic work. A total of 14,442 tokens from 2,328 unique words were analyzed. Using hierarchical cluster analysis, the students' experiences were classified into three themes: AI-assisted academic output; AI and learning engagement; and the cognitive and behavioral impacts of AI dependence. Sentiment analysis revealed that students had predominantly negative sentiments toward frequent AI tool use, driven by words such as *lazy*, *depend*, *tired*, and *unmotivate*. The Chi-square test confirmed that negative sentiments significantly outnumbered positive ones, $\chi^2(1) = 47.25$, $p < .001$. These findings suggest that while students recognize the convenience of AI tools, frequent use has led to dependence, reduced motivation, and cognitive fatigue. Implications for teaching practice and future research directions are discussed.



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I. INTRODUCTION

Students' experiences with AI tools refer to the interactions, behavioral patterns, and outcomes that emerge from sustained use of artificial intelligence for academic purposes [1]. These experiences affect how students think, learn, and behave in their academic work [2]. Considering the consequences of these experiences, they are increasingly investigated in educational contexts because students' use of AI tools can influence how they engage with their academic tasks [3]. It is important to understand students' experiences with AI tools because doing so can help educators identify the conditions under which these tools support or hinder learning [4]. Understanding these experiences promotes more informed instructional decisions, which in turn could prevent students from developing passive and dependent learning habits [2] and avoid the motivational decline and disengagement that frequently follow from over-reliance on AI tools [3]. Fatigue is another psychological consequence that affects students' academic engagement with AI tools. [5] [6] define cognitive fatigue as a state of mental exhaustion that arises when sustained engagement with a demanding task or technology depletes a student's cognitive resources. Its effects are increasingly documented in educational settings. For instance, it has been established that AI dependence has a negative influence on critical thinking [4], student motivation [1], and academic performance [2]. Understanding students' fatigue toward frequent AI tool use is important because it can lead to the implementation of appropriate teacher interventions. For example, after identifying that AI dependence contributes to cognitive fatigue, educators can develop strategies that scaffold independent thinking and reduce over-reliance on AI-generated outputs [3]. Recently, AI tools such as ChatGPT have been widely adopted at the undergraduate level. A global survey by the [7] found that 86% of college students already use AI in their studies, with ChatGPT cited as the most widely used tool among 66% of respondents, and students using an average of 2.1 AI tools for their academic work. There is a growing body of research on AI use in education that focuses on its effects on academic performance [2], student dependence [3], and cognitive engagement [4]. However, students' experiences and fatigue toward frequent AI tool use, as expressed in their own words, remain relatively unknown. The lack of understanding of these psychological dimensions leaves a significant gap in the practice of teaching and learning the responsible use of AI tools [1].

As a result, educators may be unable to identify the conditions that contribute to AI-related fatigue or to develop appropriate responses that preserve students' cognitive engagement and academic independence. To address this gap, this study was conceived. It aims to apply text mining techniques to understand students' experiences and fatigue toward frequent AI tool use. Specifically, the study aims to answer the following questions: (1) What are the students' experiences with frequent AI tool use when categorized using hierarchical cluster analysis?, and (2) How can students' fatigue toward frequent AI tool use be described when analyzed using sentiment analysis?

II. MATERIALS AND METHOD

II.1 SETTING, PARTICIPANTS, AND DATA COLLECTION PROCEDURE

The study was conducted in one university in the Philippines. Participants consisted of college students from various programs who were enrolled during the academic year in which data collection was undertaken. A total of 491 students who submitted open-ended responses written predominantly in English were included in the study. Data were collected through a structured open-ended questionnaire administered online via the university's learning management system. Students were asked to respond in writing to series of open-ended questions covering their general experiences with AI chatbots such as ChatGPT, the academic tasks for which they use these tools, and the physical, emotional, and mental fatigue associated with their frequent use, including any perceived changes in their learning habits, motivation, focus, and overall academic behavior. The responses were collected, anonymized, and consolidated into a single dataset for analysis. All data were handled in compliance with ethical standards for research involving human participants.

II.2 DATA PREPROCESSING, DATA CLEANING, AND DATA PROCESSING

The text mining procedures adopted in this study followed those established by [8], [9], who both employed open-ended survey responses as source data and applied preprocessing, hierarchical cluster analysis, and frequency-based interpretation to analyze student-generated text. The text from the series of open-ended questions was aggregated into a single document. All text was then converted to lowercase to normalize typographic variation. For instance, "AI," "Ai," and "ai" were treated as a single token. Lowercase conversion is a standard preprocessing step that reduces noise and improves the accuracy of subsequent analysis [8], [10]. Contractions such as don't, it's, and won't were also expanded by removing the apostrophe suffixes to recover their constituent word forms, after which all remaining special characters, numbers, punctuation marks, and symbols were removed, leaving only alphabetic content for further processing. The words were then lemmatized using a domain-specific manual mapping lexicon developed for this study. Lemmatization is the process of reducing different forms of a word to their base form, or lemma, as found in the dictionary. For example, motivated, motivating, and motivation were each reduced to motivate [8]. Unlike stemming, which applies rule-based truncation and can produce non-words, lemmatization preserves the meaning of the word and is considered the more appropriate normalization method for semantic tasks such as sentiment analysis and cluster analysis [11].

A total of 190 lemma mappings were developed to address the specific vocabulary patterns present in the dataset. After lemmatization, the documents were tokenized into unigrams, that is, individual words. Tokenization is a necessary step in text mining that transforms continuous text into discrete units suitable for frequency counting and further analysis [12]. Bigram analysis was also attempted. However, as observed in similar studies [8], no meaningful patterns emerged at the bigram level, and the unigram was therefore retained as the unit of analysis. The dataset was then subjected to stopwords removal in two passes. The first pass removed standard English stopwords, which are high-frequency function words that carry little to no semantic content, such as the, a, an, is, and of [12]. The second pass removed domain-specific keyword stopwords, that is, words that were highly frequent in the dataset but unhelpful for identifying thematic differences among responses. These included terms directly tied to the survey topic, such as ai, chatgpt, tool, use, experience, feel, fatigue, and student. Words of fewer than three characters were also removed. This two-pass removal follows the approach of [8], who similarly excluded course-name keywords alongside standard stopwords to isolate substantively meaningful vocabulary. The resulting corpus consisted of 14,442 tokens across 2,328 unique words. Following the pruning procedure of [8], in which words appearing fewer than five times were eliminated prior to clustering, 35 words were retained for hierarchical cluster analysis. This final step constituted the corpus used in subsequent analyses.

II.3 DATA ANALYSIS

The corpus was analyzed using two complementary text mining techniques: hierarchical cluster analysis and sentiment analysis, following the analytical framework of [8]. Both analyses were implemented in Python using the scipy, sklearn, and matplotlib libraries. The students' experiences with AI tool use were examined through hierarchical cluster analysis. Hierarchical clustering is an agglomerative method that progressively merges smaller data subsets into larger groupings, producing a tree-like structure called a dendrogram that visually represents the similarity relationships among the grouped items [13-16]. A term-document matrix (TDM) was constructed from the 35 retained words across 472 documents, with each word represented as a vector in document space. To account for differences in document length, each word vector was normalized using L2 normalization before clustering, so that the resulting Euclidean distances would reflect semantic proximity rather than simple frequency counts [9]. Clusters were then generated using Ward's minimum variance method (ward. D2), which at each step merges the pair of clusters whose joining results in the smallest increase in total within-cluster variance. Ward's method has been shown to produce more clearly defined clusters compared to alternative linkage criteria, and the combination of Euclidean distance with Ward's method is widely recommended as a reliable choice for text-based cluster analysis [9], [16]. To determine the optimal number of clusters to retain, the Elbow method was used. This method involves plotting the total within-cluster sum of squares against successive values of k and identifying the point at which the rate of decrease noticeably levels off [8]. A visual inspection of the resulting dendrogram was also conducted to verify the clarity and coherence of the cluster structure. In labeling the clusters, thematic analysis served as the guiding framework, consistent with the procedures of [8], [17].

The words within each cluster served as codes, which were then examined alongside the original sentences from which they were drawn to evaluate how well they reflected a common theme. Proposed labels were iteratively revised until consensus was reached among the research team. To examine the students' affective responses toward frequent AI tool use, particularly those related to fatigue, sentiment analysis was conducted. Sentiment analysis is a text mining technique that identifies the positive or negative orientation of words or documents to characterize the writer's feelings, emotions, attitudes, or reactions [9], [10]. In this study, sentiments were classified using the *bing* lexicon, a binary sentiment dictionary that assigns each word a positive or negative polarity [18], as employed in the original study of [8]. Words appearing fewer than three times in the corpus were excluded from the sentiment visualization for the sake of clarity and readability, following the same threshold applied by [8]. The total counts of positively and negatively labeled words were then tabulated and reported. A Chi-square goodness-of-fit test was performed to determine whether the observed distribution of positive and negative sentiments was statistically different from an equal distribution, with a significance level set at $\alpha = .01$, consistent with [8]. The Chi-square test was selected because it is appropriate for comparing observed frequencies across two categorical groups when the data are nominal and cell frequencies are sufficiently large.

III. RESULTS AND DISCUSSION

III.1 STUDENTS' EXPERIENCES THROUGH CLUSTER ANALYSIS

Table 1 shows the ten most frequently used words to express the students' experiences with frequent AI tool use in academic work. The word *answer* was the most frequently occurring, appearing 376 times. The words *understand* and *easy* were the second and third most frequently used words. The top three words are closely related to one another, suggesting that students primarily associate AI tool use with getting quick answers and making academic tasks easier to understand. The fourth most frequently occurring word was *work*, followed by *rely* and *idea*. As shown in the sample texts, students use AI tools to complete their academic work and generate ideas, but also recognize that they have developed a degree of reliance on these tools in doing so. Students perceived AI tools as relevant to accomplishing their academic requirements. As such, they came to rely on these tools regularly. Specifically, students depend on AI tools because they believe these tools help them finish academic tasks more conveniently. The word *depend* further reinforces this pattern, appearing 151 times in the corpus. Notably, the word *lazy* appeared 132 times, suggesting that students are already aware of the behavioral changes that frequent AI tool use has brought about. These findings are consistent with those of [3], who found that increased laziness and reduced independent thinking were among the most frequently reported negative effects of AI dependency among university students.

Table 1: Ten most frequently used words in the corpus.

Rank	Words	Frequency	Sample Sentence
1	answer	376	I usually ask AI to answer my questions, especially for assignments.
2	understand	339	I use AI to help me understand difficult lessons more easily.
3	easy	227	AI makes it easy to complete tasks without much effort.
4	work	210	It helps me finish my work faster, but I tend to rely on it too much.
5	rely	197	I rely on AI whenever I encounter difficult topics.
6	idea	196	I ask AI to generate ideas for my essays and assignments.
7	lesson	173	I use AI to understand lessons I missed or did not fully grasp in class.
8	ask	161	I ask AI to explain things I do not understand in my subjects.
9	depend	151	I have become dependent on AI; I can no longer think independently.
10	topic	143	AI helps me research various topics more efficiently.

Source: Authors, (2026).

The optimal number of clusters to retain was three (Figure 1). The hierarchical cluster analysis confirmed the three clusters (Figure 2). The words *idea*, *essay*, *check*, *grammar*, and *write* comprised the first cluster. The cluster was labeled “*AI-Assisted Academic Output*” (Table 2) after an examination of the sentences that contained these words. Sample sentences in this cluster include “*I use AI to generate ideas for my essays when I do not know what to write*” and “*I rely on AI to check my grammar and correct my writing before submitting.*” Based on these sentences, the cluster reflects the students' use of AI tools as a direct aid in producing academic outputs.

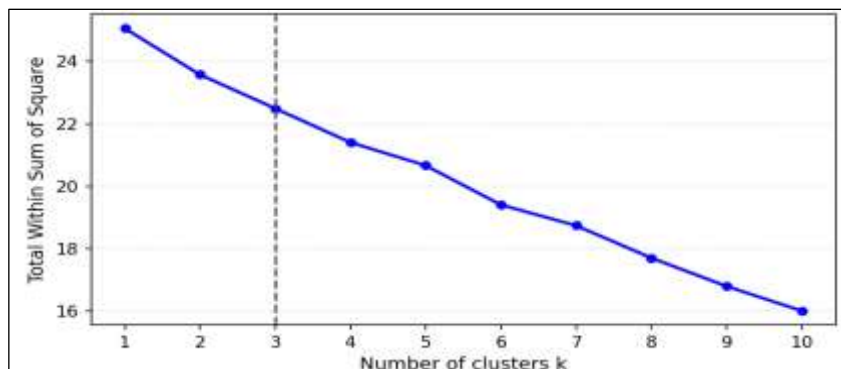


Figure 1: Elbow Method showing the optimal number of clusters.

Source: Authors, (2026).

Cluster 2 contained the words *understand, rely, lesson, topic, tired, motivate, focus, read, and notice*. The cluster was labeled “*AI and Learning Engagement*.” Sample sentences in this cluster include “*I use AI to understand lessons I find difficult, but I notice I no longer feel motivated to read on my own*” and “*Because AI can explain topics faster, I have become less focused when studying*.” Based on these sentences, the cluster reflects a more nuanced set of experiences, where students acknowledge the helpfulness of AI tools in understanding academic content while also recognizing that frequent use has affected their motivation and focus. The appearance of the word *tired* in this cluster is particularly notable. It suggests that engaging with AI tools, while initially helpful, eventually contributes to a sense of fatigue related to learning. This finding supports [4], who found that AI dependence was associated with lower levels of critical thinking, with cognitive fatigue serving as a partial mediating mechanism. The co-occurrence of *tired* and *rely* in the same cluster in the present study reflects a similar dynamic, wherein reliance on AI tools gradually erodes students’ motivation and cognitive engagement. The last cluster was labeled “*Cognitive and Behavioral Impacts of AI Dependence*.” The cluster label was supported by sentences containing the words *answer, easy, work, ask, depend, lazy, information, assignment, affect, become, negative, unmotivate, question, find, research, explain, give, subject, knowledge, want, and problem*. For instance, one student said, “*I have become so dependent on AI that I no longer make an effort to find answers on my own*.” Another student stated, “*AI has made me lazy; I just ask it everything instead of thinking for myself*.” The prominence of words such as *lazy, depend, unmotivate, and negative* in this cluster corroborates the findings of [3], who identified increased laziness and reduced independent thinking as the most frequently self-reported consequences of AI dependency among college students.

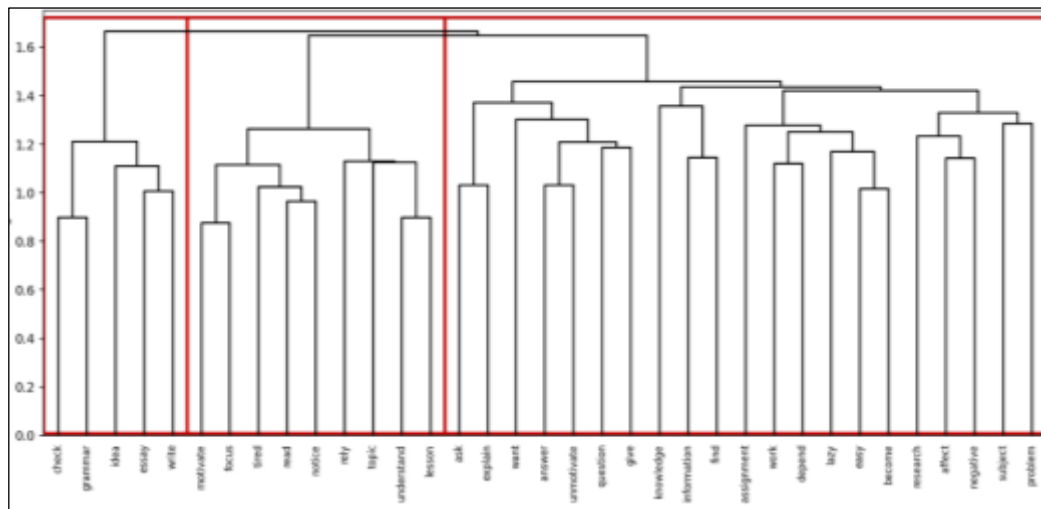


Figure 2: Hierarchical cluster analysis of words.

Source: Authors, (2026).

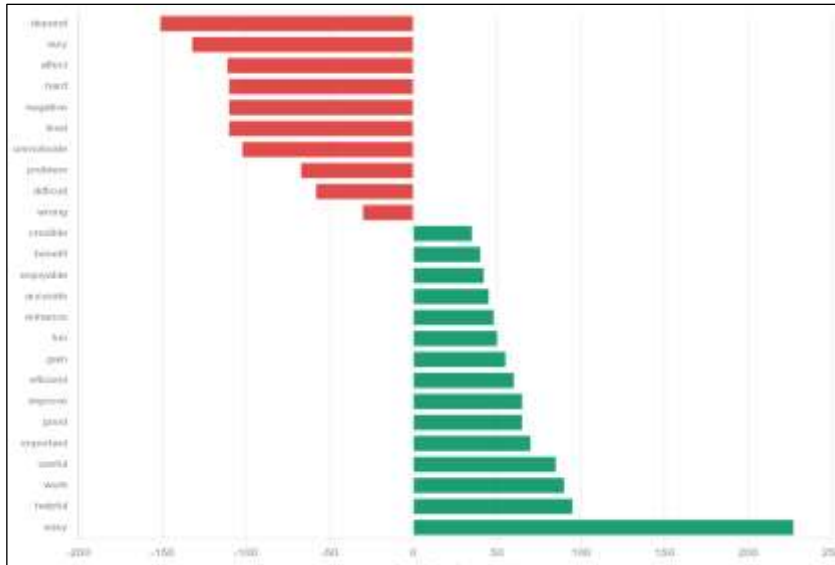
Table 2: Labels of hierarchical clusters.

Cluster 1 - AI-Assisted Academic Output	Cluster 2 - AI and Learning Engagement	Cluster 3 - Cognitive and Behavioral Impacts of AI Dependence
idea	understand	answer,
essay	rely	easy
check	lesson	work
grammar	topic	ask
write	tired	depend
	motivate	lazy
	focus	information
	read	assignment
	notice	affect
		become
		negative
		unmotivate
		question
		find
		research
		explain
		give
		subject
		knowledge
		want
		problem

Source: Authors, (2026).

III.2 STUDENTS' FATIGUE ANALYZED USING SENTIMENT ANALYSIS

One hundred and eighty-five words were labeled with sentiments using the *bing* dictionary. As shown in Figure 3, the word *easy* had the highest number of contributions in the positive sentiments ($n = 227$). One student said, “*AI makes it easy to finish assignments without spending too much time.*” In another statement, “*It is easy to understand lessons when AI explains them in a simple way.*” These statements reflect the students’ appreciation of the convenience that AI tools provide in academic tasks. This finding is consistent with [19], whose meta-analysis of 69 experimental studies found that ChatGPT use generally improves students’ affective-motivational states, including their perception that tasks are more manageable. Meanwhile, the word *lazy* contributed the most to negative sentiment. This negative sentiment was mainly attributed to the behavioral consequences of frequent AI tool use. For example, one student said, “*I have become lazy because AI does everything for me, so I no longer think on my own.*” Another student noted, “*AI has negatively affected my study habits because I just depend on it instead of doing the work myself.*” Students in this study expressed similar sentiments to those documented by [4], who found that students with higher AI dependence reported greater cognitive fatigue, which in turn diminished their motivation and critical thinking capacity. Furthermore, this supports the findings of [3], who discovered that students experiencing AI dependency consistently reported becoming lazier and less capable of independent thought.



Of the three clusters, the cognitive and behavioral impacts cluster contained the highest number of words, indicating that students placed the greatest emphasis on the negative consequences of frequent AI tool use. Sentiment analysis further confirmed this pattern. Students felt that frequent use had made them lazy, dependent, and unmotivated to engage with academic tasks independently. Negative sentiments significantly outnumbered positive ones. Hence, while students acknowledged the convenience of AI tools, their overall sentiments pointed to fatigue, reduced motivation, and diminished cognitive engagement as the more dominant outcomes of frequent use. Educators are advised to design learning activities that position AI tools as supplements to rather than substitutes for independent thinking. Teachers may conduct brief self-assessments of students' AI use patterns at the start of the course and use the results to adjust their instructional strategies accordingly. Reflection tasks that require students to attempt problems on their own before consulting AI tools may also help reduce over-reliance and foster metacognitive awareness. Future research may include students from other institutions and degree programs to test the generalizability of these findings. A longitudinal design tracking changes in students' experiences and sentiments across a full semester would offer a clearer picture of how AI-related fatigue develops over time. Finally, a more detailed form of sentiment analysis capturing specific emotional states such as frustration, anxiety, and boredom, as well as other text mining approaches such as topic modeling and word association analysis, are also recommended for future investigation.

V. AUTHOR'S CONTRIBUTION

Conceptualization: John Paul P. Miranda.

Methodology: John Paul P. Miranda.

Investigation: John Paul P. Miranda.

Discussion of results: John Paul P. Miranda.

Writing – Original Draft: John Paul P. Miranda.

Writing – Review and Editing: John Paul P. Miranda.

Resources: John Paul P. Miranda.

Supervision: John Paul P. Miranda.

Approval of the final text: John Paul P. Miranda.

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