Predicting Academic Amotivation from ChatGPT Use Among a Cohort of Kuwaiti Undergraduates

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Abstract

Based on Self-Determination Theory (SDT), this study was designed to test whether ChatGPT use predicts academic amotivation, and to examine age and gender differences in these variables using a sample of Kuwaiti undergraduates. A cross-sectional online survey was conducted with 222 students at the Public Authority for Applied Education and Training. Data were analyzed using non-parametric tests and linear regression. Findings indicated that while females reported slightly higher, though non-statistically significant ChatGPT use, males showed significantly greater academic amotivation (U = 3585.50, p = 0.016). Regression analysis revealed that ChatGPT use was a small but significant predictor of academic amotivation (β = 0.202, p = 0.003), explaining 4.1% of the variance. The results suggest that while AI tools can offer support, increased reliance may correlate with diminished academic engagement. This study underscores the need for educational strategies that promote a balanced and critical integration of AI to support rather than undermine student motivation.

Keywords: ChatGPT, Academic Amotivation, Self-Determination Theory, Motivation, Higher Education

1. Introduction

The quick and widespread use of generative artificial intelligence (AI), especially ChatGPT, in higher education has led to a need for a closer look at how it affects student motivation. Since its public launch in late 2022, many university students have adopted ChatGPT for varying academic tasks. These include brainstorming, drafting, summarizing, problem-solving, and editing (Kasneci et al., 2023). A cross-sectional survey conducted among 23,218 students from 109 nations and territories revealed that ChatGPT was widely used (71%) by undergraduate students worldwide (Ravšelj et al., 2025). In a study among 1,041 students in the United Kingdom, findings show that 92% of respondents utilise AI (Freeman, 2025). An online survey completed by 737 undergraduate students from a Spanish institution indicated that 70% of respondents use ChatGPT for both personal and academic reasons (Blahopoulou & Ortiz-Bonnin, 2025). A study based on data from the 2024 China College Student Survey (CCSS 2024) collected responses from 72,615 undergraduate students at 25 universities and colleges in China. It reported that 64.47% of respondents used GenAI technologies (Guo et al., 2025). In a study among 548 Hungarian high school students, 16% of respondents used artificial intelligence to write their text-based homework projects (Turós et al., 2025). Indeed, the number of students using AI tools for schoolwork has grown significantly since 2023, making generative AI a common part of college learning.

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While early discussions often praised its ability to provide access to quality feedback and personalized support, some critics warn that over-reliance on ChatGPT could detract from the deep cognitive engagement that is crucial for real learning and skill development (Fan et al., 2025; Heung & Chiu, 2025; Yang et al., 2024). This debate reflects the longstanding tension between enhancement and replacement. Evidence regarding the overall effect of AI on learning outcomes is mixed. For instance, a systematic review of 14 studies revealed a dual-edged impact of ChatGPT use in education (Albadarin et al., 2024). On the positive side, ChatGPT functioned effectively as an intelligent virtual assistant, offering instant feedback, tailored explanations and resource access. Conversely, the review highlighted several negative implications associated with excessive reliance on the tool, which may suppress students' creativity, critical thinking, and collaborative engagement in group learning contexts (Albadarin et al., 2024). Another review of 69 scholarly studies revealed that ChatGPT use improves academic performance, affective motivation and higher-order thinking, reduces mental effort and has no significant influence on students' self-efficacy (Deng et al., 2025). A systematic review of 63 studies bordering on AI use in higher education found that such use generally enhances cognitive and affective learning outcomes, but their effects on skill development and higher-order cognitive processes are inconsistent (Luo et al., 2025).
In an experimental study involving 92 university students in Germany, results showed that ChatGPT users experienced significantly lower cognitive load, but their reasoning and argumentation quality were lower than that of Google users (Stadler et al., 2024). The study suggests that ChatGPT use can ease mental effort during information gathering, but it may limit deeper cognitive engagement and reasoning quality. Taken together, these findings highlight a critical issue: AI tools like ChatGPT may make learning more accessible, but without careful integration into the learning process, they risk reducing students' cognitive depth and ownership of learning.

Understanding these dynamics calls for a motivational framework. Self-Determination Theory (SDT), developed by Deci & Ryan, provides a useful framework for understanding the psychological mechanisms by which technological environments affect academic performance (Deci & Ryan, 1985). SDT distinguishes between intrinsic motivation, which comes from genuine interest, different types of extrinsic regulation, which rely on external rewards or obligations, and amotivation. Amotivation is a feeling of disinterest, lack of intention or helplessness where people see academic tasks as irrelevant or out of their control (Deci & Ryan, 2008; Ryan & Deci, 2000; Ryan & Deci, 2018). Academic amotivation can predict lower persistence, higher dropout rates and poorer academic performance (Legault et al., 2006). According to SDT, environments that do not foster autonomy, competence or relatedness tend to cause amotivation, while those that support these psychological needs promote self-directed motivation (Ryan & Deci, 2018).

The application of SDT to digital learning has produced mixed findings, similar to the evidence on AI's effect on learning outcomes. Empirical findings indicate that motivation plays a central mediating role that explains why students choose to continue engaging in online self-regulated learning (Luo et al., 2021). ChatGPT use was found to improve affective motivation (Deng et al., 2025). A longitudinal survey involving 323 Chinese university students indicate that both the interaction quality and output quality of generative AI (GAI) use exerted significant positive effects on students' learning motivation (Bai & Wang, 2025). Yet, some studies reveal that excessive use of digital media, especially tools that automate or simplify cognitive tasks, can weaken motivation, focus, and academic self-efficacy (Dolan, 2025; Fan et al., 2025). An experimental study involving 117 university students found no significant differences in post-task intrinsic motivation across learning support conditions, including ChatGPT use (Fan et al., 2025).

Excessive reliance on AI tools may lead students to feel disconnected from their academic identity, reducing ownership and competence which are key predictors of amotivation (Jia et al., 2025; Zhang et al., 2024). Amotivation is a critical yet underexplored outcome of AI use in education. Students who over-rely on AI may think less critically (Vieriu & Petrea, 2025), deplete their skill-set (Hasanein & Sobaih, 2023), diminish their interpersonal skills and emotional intelligence (Klimova & Pikhart, 2025) and engage in academic dishonesty (Vieriu & Petrea, 2025). Consequently, they may become psychologically detached from learning goals, highlighting the need to study contextual and demographic factors such as age and gender.

Globally, AI adoption in education manifests a significant contextual and cultural variation. While AI has spread worldwide, research is unevenly distributed, with limited evidence from the Gulf Cooperation Council (GCC) states. Kuwait is particularly noteworthy. The country aims to build a national AI strategy that promotes integration of AI technologies across sectors, fosters national talent with advanced technical skills, and aligns with Vision 2035 to diversify the economy and strengthen innovation (Kuwait Government Online News, 2025). Yet, AI adoption levels remain moderate in Kuwait and related countries; a multinational survey across Kuwait, Iraq, Egypt, Lebanon, and Jordan found that only 46.8% of students had heard of ChatGPT (Abdaljaleel et al., 2024). As of 2025, data on ChatGPT use and its motivational effects among Kuwaiti undergraduates are very limited. Examining this population will contribute valuable insights into how cultural context influences AI adoption and academic motivation. This study therefore addresses a clear research gap: the relationship between ChatGPT use and academic amotivation in a Kuwaiti undergraduate context, guided by SDT. Specifically, it investigates three questions: 1. What are the main patterns of ChatGPT use and levels of academic amotivation? 2. Do age and gender affect students' ChatGPT use and amotivation? 3. Can ChatGPT use predict academic amotivation? The study variables in these research questions are represented in the conceptual framework (Figure 1.). By answering these questions, this study offers three key contributions. First, it provides new empirical evidence on the link between ChatGPT use and academic amotivation in Kuwait which is an understudied context within the GCC. Second, it adds nuance by examining how age and gender shape ChatGPT use and motivational outcomes in a non-Western setting. Third, it employs Self-Determination Theory to illuminate the potential motivational risks of AI reliance, offering a theoretically grounded perspective.
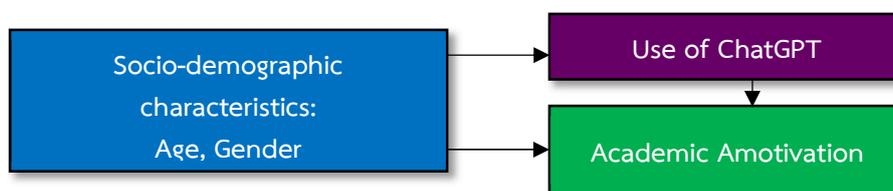

Figure 1. Conceptual Framework.

2. Research Objectives

1. To examine the main patterns of ChatGPT use and the levels of academic amotivation among undergraduate students.

2. To determine whether age and gender significantly influence students' ChatGPT use and their levels of academic amotivation.

3. To assess whether ChatGPT use predicts students' academic amotivation.

3. Research Methodology

3.1 Study Design

This study is a quantitative, cross-sectional survey aimed at examining patterns of age cum gender differentials in, and the relationship between the use of ChatGPT and academic amotivation during a single period of data collection.

3.2 Participants and Sampling

The target population for this study included all undergraduate students enrolled at the Public Authority for Applied Education and Training (PAAET) during the second semester of the 2024/2025 academic year. PAAET is one of Kuwait's largest providers of vocational and technical education, with about 17,459 students registered in its programs, according to recent statistics (Wikipedia, 2025). This number was used as the working population size (N) to estimate the required sample size. Sample size determination was done using the Sample Size Calculator (Calculator.net, n.d.). Based on a population of 17,459, a 95% confidence level, a 50% assumed population proportion, and a 6.5% margin of error, a minimum sample size of 225 respondents was calculated to be sufficient for achieving statistical representation.

Data collection utilized a self-administered online questionnaire developed on Google Forms. A voluntary sampling method was used, where the survey link was shared through institutional channels like official email lists and student WhatsApp groups. The opening section of the form included detailed information about the study's purpose, estimated completion time and promises of confidentiality. An informed consent statement outlining participants' rights, the voluntary nature of participation, anonymity and data usage was also included. Only respondents who agreed by selecting "I agree to participate" were allowed to continue responding to the questionnaire.

The survey was open for nearly four weeks. Responses were monitored to ensure adequate participation, and data collection ended once the minimum threshold of 225 responses was reached. The dataset was then exported as a comma-separated values (CSV) file and later imported into SPSS for statistical analysis. To maintain confidentiality, no personally identifiable information was collected, and the dataset was protected with a password. After an initial review, three cases with excessive missing data were removed, resulting in a final sample of 222 valid responses for analysis.

3.3 Instrument of Data Collection

The study used a structured online questionnaire designed to assess the constructs of interest. Details of the scales used to measure variables are described further:

1. Operational Definition of Variables and Measurement

The use of ChatGPT was operationalized as the self-reported frequency with which students utilized ChatGPT for academic purposes over the past month. It was measured through an author-developed five-item scale that asked respondents to indicate how many times they had engaged with ChatGPT for academic work (see Figure 2.). The responses were aggregated to form a composite measure of ChatGPT use. The reliability analysis of the scale indicated a Cronbach's alpha coefficient of 0.899 across the five items, demonstrating high internal consistency and suggesting that the scale is reliable.

To establish the convergent validity of the scale, it was correlated with the four-item Perceived Importance of Technology scale (Svenningsson et al., 2022). Results showed a positive, significant association (Spearman's $r = 0.144$, $p = 0.032$), indicating that higher perceived technology importance is linked to greater ChatGPT use, thereby supporting the scale's validity.

Academic amotivation was operationalized as the extent to which respondents experience a lack of purpose in pursuing their academic studies. It was measured with the 4-item academic amotivation subscale of the 28-item academic motivation scale (Vallerand et al., 1992). Respondents were asked to rate how well each statement in the scale reflected their own thoughts and feelings about attending school (see Figure 3.). The items were rated on a 5-point scale (1 = does not correspond at all to 5 = corresponds strongly). Scores were computed by adding responses across all items, with higher scores indicating stronger levels of academic amotivation. The scale demonstrated excellent internal consistency in the present study, with a Cronbach's alpha of 0.903 across the four items. Consistent with the scale's design by Vallerand et al. (1992), the 4-item subscale was treated as a unidimensional construct. Previous authors including Utvær & Haugan (2016), have also confirmed the reliability and construct validity of the AMS across diverse educational settings, further supporting the appropriateness of its use in this study. Sex and age were assessed nominally.

2. Study Hypotheses

H_{01}: There is no significant difference in the use of ChatGPT across respondents' age groups.

H_{11}: There is a significant difference in the use of ChatGPT across respondents' age groups.

H_{02}: There is no significant difference in academic amotivation across respondents' age groups.

H_{12}: There is a significant difference in academic amotivation across respondents' age groups.

H_{03}: There is no significant gender difference in the use of ChatGPT among respondents.

H_{13}: There is a significant gender difference in the use of ChatGPT among respondents.

H_{04}: There is no significant gender difference in academic amotivation among respondents.

H_{14}: There is a significant gender difference in academic amotivation among respondents.

H_{05}: The use of ChatGPT does not significantly predict academic amotivation among respondents.

H_{15}: The use of ChatGPT significantly predicts academic amotivation among respondents.

3.4 Method of Data Analyses

Descriptive statistics (frequencies and percentages) were computed to summarize respondents' demographic characteristics and general response trends. To examine group differences, non-parametric tests were employed because of the non-normality of the distributions of Use of ChatGPT and Academic Amotivation. The Kruskal–Wallis H test was used to assess age-related differences, and the Mann–Whitney U test was used to determine gender-based variations in the two continuous variables, both of which assumed the status of dependent variables in the context of the analysis of group differences.

Data screening before regression analysis indicated deviations from normality, with Use of ChatGPT and Academic Amotivation showing skewness values of 0.85 and 0.90, respectively. To address these violations while maintaining data interpretability, Templeton's two-step transformation was applied. This is because linear regression was preferred for the predictive analysis due to its superior explanatory power in modeling relationships between variables. To meet the normality assumption of regression, the transformation was necessary. Templeton's procedure improved the distributional properties of the variables. The transformed scores showed reduced skewness and kurtosis (e.g., Normalized ChatGPT Use: skewness = 0.26, kurtosis = −0.66; Normalized Academic Amotivation: skewness = 0.86, kurtosis = −0.02), indicating a closer approximation to normality, particularly for the ChatGPT Use variable. The monotonic nature of the transformation preserved the ordinal integrity of the data while enhancing suitability for parametric analysis.

Finally, a simple linear regression analysis was conducted to test whether the Use of ChatGPT significantly predicted Academic Amotivation. Standardized (β) coefficient and Pearson's r were used to examine the strength and direction of the relationship. The coefficient of determination (R^2) and the F statistic were reported to evaluate model fit, while statistical significance was determined at $p < .05$. Data analysis was conducted using the Statistical Package for the Social Sciences (SPSS, version 25).

4. Results

4.1 Results of the Examination of ChatGPT Use Patterns and Academic Amotivation among Undergraduate Students

1. Demographic characteristics of respondents

The socio-demographic characteristics of the respondents revealed that the majority were young adults aged 18–21 years (76.1%), while smaller proportions fell within the 22–25 years (16.7%), 26–29 years (3.6%), and 30 years and above (3.6%) categories. With respect to gender, the distribution shows a clear predominance of females (85.1%) compared to males (14.9%).

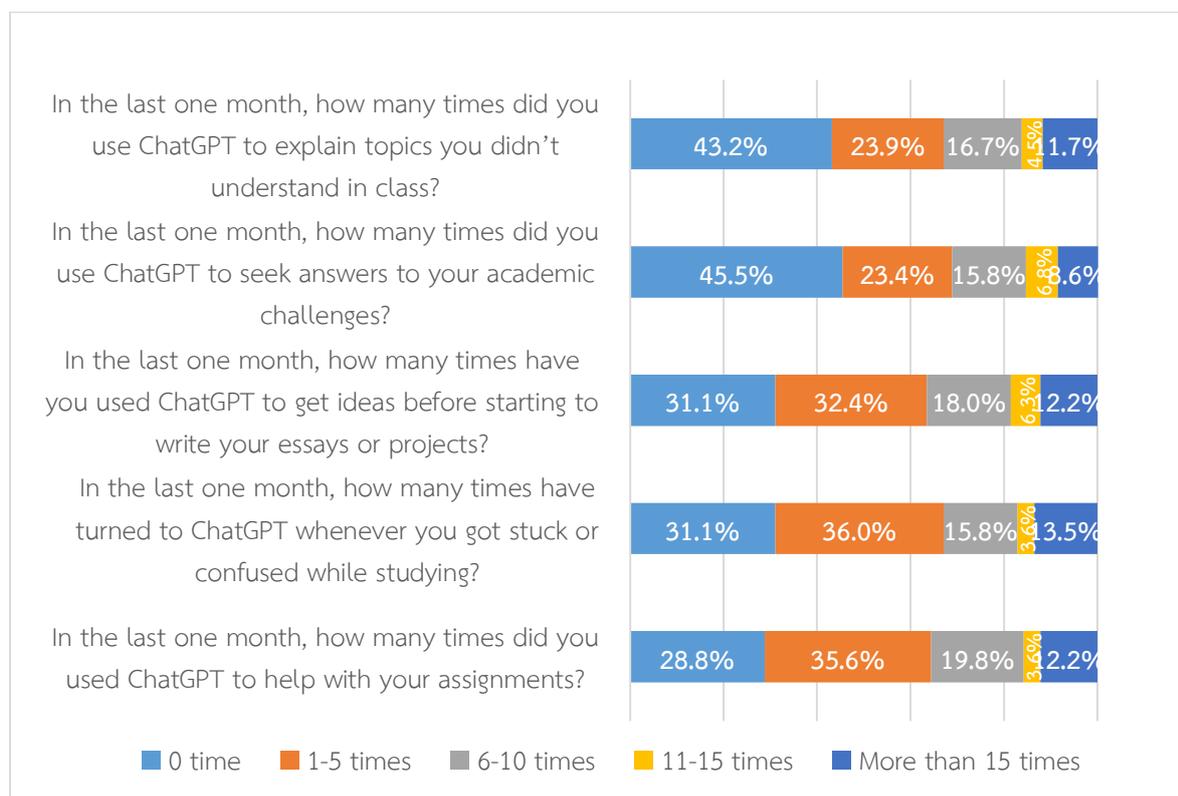**2. Use of ChatGPT Among Respondents**

Figure 2. Item-based analysis of ChatGPT use among respondents.

Figure 2. shows a stacked bar chart of how often respondents reported using ChatGPT in the month before the survey. Across all study-related activities, a clear pattern of low-to-moderate usage emerges. A significant number of respondents indicated that they did not use the tool at all for any activity measured. The highest rate of non-use was related to seeking answers to academic challenges at 45.5%, while the lowest was 28.8% for using the tool as an assistant with assignments. For all activities, most

respondents reported using ChatGPT 1 to 5 times. Higher usage frequencies (6-10 times, 11-15 times, and more than 15 times) consistently accounted for a minority of responses across all tasks. However, the highest frequency of use (more than 15 times combined) was noted for getting unstuck while studying at 13.5%. Overall, the findings show that ChatGPT is being used for various academic tasks, with infrequent to low-moderate usage being the most common pattern among users in this study.

3. Academic Amotivation among respondents
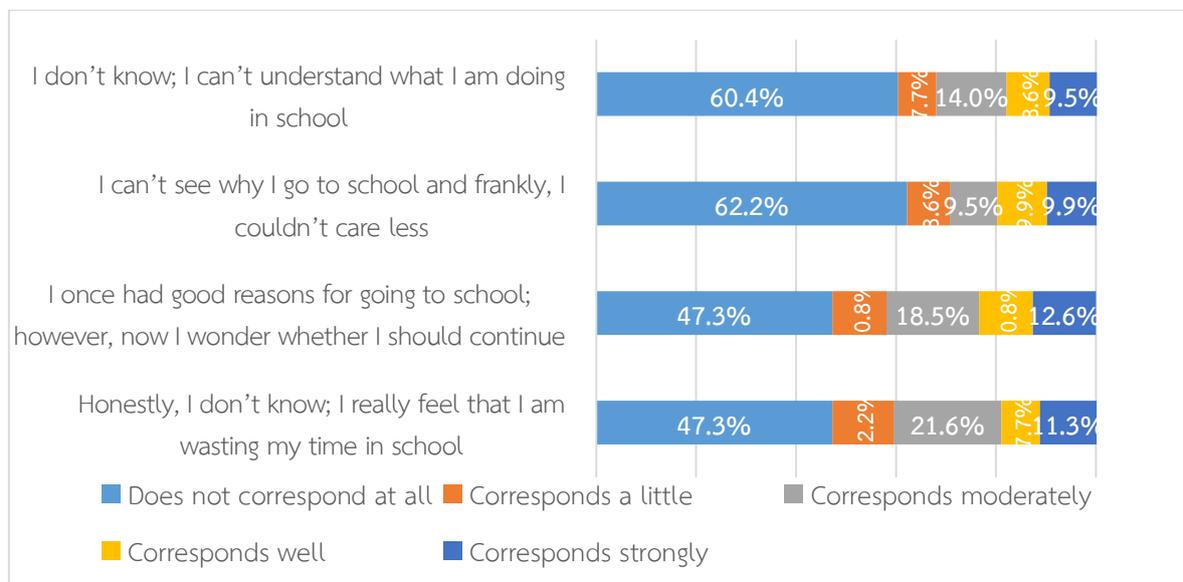
Figure 3. Analysis of items in the scale of Academic Amotivation among Respondents.

Figure 3. is a stacked bar chart that shows the response distribution for items measuring academic amotivation. The overall pattern indicates that amotivation was generally low among respondents. Most respondents selected "does not correspond at all" for all items, with percentages ranging from 47.3% to 62.2%. This reflects a high alignment with academic motivation. In contrast, a smaller group of respondents, around 9.5% to 21.6%, reported moderate to strong correspondence with these items. This indicates varying levels of academic motivational decline, suggesting that a specific segment of the student population is at risk of academic disengagement.

5.2 The Influence of Age and Gender on the Use of ChatGPT and Academic Amotivation

1. The Influence of Age on the Use of ChatGPT and Academic Amotivation

The descriptive patterns in the mean ranks presented in Table 1. suggest a gradual increase in both the Use of ChatGPT and Academic Amotivation with age. Specifically, participants aged 30 years and above recorded the highest mean ranks for Use of ChatGPT (Mean Rank = 139.50) and Academic Amotivation (Mean Rank = 121.00), whereas those aged 22–25 years had the lowest ranks (Mean Rank = 105.62 and 99.49, respectively). This trend indicates that older participants tended to report slightly higher ChatGPT use and amotivation levels compared to their younger counterparts. However, results from the Kruskal–Wallis tests revealed that these observed differences were not statistically significant for either variable: Use of ChatGPT ($H = 2.50$, $df = 3$, $p = 0.476$) and Academic Amotivation ($H = 1.78$, $df = 3$, $p = 0.620$). Thus, although minor age-related variations were evident in the descriptive data, age did not exert a significant influence on participants' ChatGPT use or their level of academic amotivation.

Thus, H_{01} and H_{02} were retained, suggesting that age did not exert a significant influence on either ChatGPT use or academic amotivation.

Table 1. Age-Based Variations in ChatGPT Use and Academic Amotivation.

	Age	Mean Rank	Kruskal Wallis Test		
			Kruskal-Wallis H	df	P value
Use of ChatGPT	18-21	110.62	2.50	3	0.476
	22-25	105.62			
	26-29	129.19			
	30 & above	139.50			
Academic Amotivation	18-21	113.38	1.78	3	0.620
	22-25	99.49			
	26-29	117.94			
	30 & above	121.00			

2. The Influence of Gender on the Use of ChatGPT and Academic Amotivation

The descriptive results presented in Table 2. indicate slight gender differences in both Use of ChatGPT and Academic Amotivation. Female participants reported a higher mean rank for Use of ChatGPT (Mean Rank = 113.16) compared to their male counterparts (Mean Rank = 101.98), suggesting that females tended to use ChatGPT more frequently. Conversely, males exhibited a higher mean rank for Academic Amotivation (Mean Rank = 125.65) relative to females (Mean Rank = 109.03), indicating a greater tendency toward academic disengagement among male participants. However, results from the Mann–Whitney U tests revealed that the gender difference in Use of ChatGPT was not statistically significant (U = 2804.50, p = 0.354). In contrast, the gender difference in Academic Amotivation was statistically significant (U = 3585.50, p = .016), showing that males were significantly more academically amotivated than females. Hence, the retention of H_{03} and the rejection of H_{04}

Table 2. Gender-Based Variations in ChatGPT Use and Academic Amotivation.

	Gender	Mean Rank	Independent-Samples Mann-Whitney U Test	
			Test statistic	P value
Use of ChatGPT	Male	101.98	2804.50	0.354
	Female	113.16		
Academic Amotivation	Male	125.65	3585.50	.0160
	Female	109.03		

5.3 Predictive Influence of ChatGPT Use on Academic Amotivation

The Use of ChatGPT significantly predicts Academic Amotivation among respondents. As shown in Table 3., this use accounted for 4.1% of the variance in academic amotivation (R^2 = 0.041, Adjusted R^2 = 0.036), indicating a modest but meaningful explanatory power. The standardized regression coefficient was positive and statistically significant (β = 0.202, p = .003; 95% CI: 0.037, 0.171), indicating that for every one standard deviation increase in ChatGPT use, academic amotivation increases by approximately 0.20

standard deviations. The overall model was statistically significant (F = 9.35, p = 0.003), confirming that ChatGPT use is a significant predictor of academic amotivation. The zero-order correlation between Use of ChatGPT and Academic Amotivation was also positive and significant (r = 0.202, p = .001), reinforcing the observed linear relationship. Hence, H_{05} was rejected.

Table 3. Result of Linear Regression Analysis Showing Use of ChatGPT as a Predictor of Academic Amotivation.

Statistic	Value
R^2	0.041
Adjusted R^2	0.036
R^2 Change	0.041
Standardized β	0.202
p value (β)	0.003
95.0% Confidence Interval for β	0.037 - 0.171
F statistic	9.35
p value (F)	0.003
Zero-order correlation	0.202
p value (Zero-order correlation)	0.001

Dependent variable: Academic Motivation

5. Conclusion

This study provides important insights into the interplay between generative AI and student motivation in Kuwait. The use of ChatGPT and academic amotivation does not vary significantly by age among higher education students. On a mixed note, while gender variation in ChatGPT use does not appear to exist, gender exerts significant variation on academic amotivation with male students being significantly demotivated. This finding is particularly noteworthy given that it suggests they male students may be a more vulnerable subgroup. Increasing ChatGPT use appears to be positively consequential for lowered motivation for academic goals. This does not imply that ChatGPT use causes amotivation but rather suggest a pattern of reliance on the tool is associated with lower levels of academic engagement. From the lens of Self-Determination Theory, such reliance could potentially undermine the satisfaction of core psychological needs for competence and autonomy. Hence, while tools like ChatGPT can provide support and improve efficiency, over-reliance may lead to a loss of motivation if not combined with reflective and self-directed learning. Educators and educational institutions should therefore encourage balanced ChatGPT use that supports, rather than replaces students' cognitive and motivational engagement.

6. Discussion

This study was designed to examine patterns of, and differentials in age and gender with regard to the use of ChatGPT and the exhibition of academic amotivation among a cohort of Kuwaiti undergraduates, including the prediction of ChatGPT use and academic amotivation.
Findings showed a low to moderate pattern of ChatGPT use for varying academic tasks, with most respondents reporting fewer than five times of use in a month. Notably, the highest use was about

"getting unstuck while studying," suggesting an emerging trend where university students dominantly use generative AI for short-term help instead of ongoing learning support. Further, the moderate usage suggests that while ChatGPT is becoming more popular globally, it has not yet replaced traditional learning in the study population. Such limited use might stem from the relative newness of generative AI in Kuwait's higher education system. The earlier cited multinational survey in the Arab region, where about half of the respondents had ever heard of ChatGPT (Abdaljaleel et al., 2024), attests to this relative newness.

Findings further indicate that academic amotivation was generally low among the undergraduates surveyed. Most respondents said that statements about amotivation did not reflect their experiences. This suggests that most students feel purposeful and engaged with their academic goals. However, a minority of respondents (9.5% to 21.6%) reported moderate to strong agreement with amotivation items. This subgroup seems to have some disconnect from their academic goals. They may be unsure about the relevance or value of their studies, suggesting emerging doubts and weaker commitment. These students are an important group whose academic persistence may be at risk. This highlights the need for further investigation into the contextual or psychosocial factors that may be affecting their motivation. Current findings show a gradual increase in both ChatGPT use and academic amotivation with age. Participants aged 30 and older had the highest average ranks in both areas; however, these differences were not statistically significant. This suggests that age did not have a major impact on either ChatGPT use or academic amotivation in this study.

This outcome generally matches recent evidence indicating that demographic factors like age are often weak predictors of generative AI use (Barrios & Déri, 2025), depending on the context. For example, a study of 507 university students in Spain by Galindo-Domínguez et al. (2024) found that age did not significantly influence ChatGPT use for academic purposes. Similarly, Baidoo-Anu et al. (2024) reported no significant link between age and perceptions of ChatGPT among 277 university students in Ghana. In contrast, a cross-national survey involving 2,240 Arab students indicated that older age was significantly linked to lower ChatGPT usage (Abdaljaleel et al., 2024). Additionally, Korchak et al. (2025) found a significant negative relationship between age and the intention to use ChatGPT among 271 university students in the United Arab Emirates. While the current results show that age does not significantly predict ChatGPT use, the mixed evidence across different contexts reflects an ongoing debate among scholars about the degree to which age affects engagement with AI tools. These differences might stem from variations in technological exposure, educational settings and digital confidence rather than from age itself.

Current findings show a slow rise in academic amotivation as students get older. However, the differences were not statistically significant, indicating that age did not have a significant effect on academic amotivation in this sample. This result matches broader trends in educational psychology. Ishida and Sekiyama's review of 84 studies found that demographic factors like age rarely account for significant differences in learners' motivation (Ishida & Sekiyama, 2024). Instead, motivation is more influenced by perceived competence, autonomy, and environmental support, which reflect the social and cultural backgrounds in which learning takes place. Meanwhile, some evidence suggests that younger undergraduates may experience higher levels of academic amotivation, though the research supporting this is limited. In a large international study with 1,711 students aged 18 to 61, Šimonji Černak et al. (2024) asserted that "internal motivation is less developed in younger age groups," suggesting that younger learners may have lower intrinsic motivation and, as a result, higher amotivation. On the other hand,

Litvinova et al. (2015) found no significant link between age and academic self-handicapping, which is a related concept, in a study among 440 Nigerian undergraduates. Similarly, the study by Fatima et al. (2018) on academic amotivation focused on small age groups (18 to 23 years) and did not directly investigate the effects of age. Overall, these findings imply that while there may be age-related trends in academic amotivation, the evidence is still unclear and needs more exploration.

The lack of a significant gender difference in ChatGPT use in this study matches growing global evidence that shows similar technology adoption trends among male and female students, especially in higher education. Morell-Mengual et al. (2025) found no gender differences in generative AI use among 974 Spanish students. Similarly, Sergeeva et al. (2025) reported that gender was not a key factor in AI adoption among 379 undergraduates at Pyatigorsk State University in Russia. Similar findings were seen in Ghana, where Baidoo-Anu et al. (2024) found no significant link between gender and perceptions of ChatGPT among 277 university students in Ghana. In the UAE, Korchak et al. (2025) also reported no gender difference in the intention to use ChatGPT among 271 students. However, Galindo-Domínguez et al. (2024) found that male students used ChatGPT more for academic purposes in a study of 507 Spanish undergraduates. This suggests that local or contextual factors might still influence gender patterns of use. Overall, the evidence suggests a closing gender gap in digital engagement, showing more equality in technology access and use across genders.

In this study, a clear gender difference in academic amotivation was found, with males reporting significantly higher levels than females. This aligns with established patterns in motivation research. Evidence shows that male undergraduates usually show more academic amotivation than their female peers. Two studies that examined this relationship, involving a total of 1,238 participants, revealed significantly higher amotivation among males (Ajlouni, 2022; Ayhan & Karacan Özdemir, 2024). Ajlouni's (2022) study of 433 Jordanian students in online learning found that males were significantly more amotivated. Similarly, Ayhan & Karacan Özdemir's (2024) research involving 805 Turkish students during the COVID-19 pandemic revealed significantly lower amotivation among females. These results match other literature indicating that females typically report higher academic motivation (Brouse et al., 2010). While there are few studies specifically looking at gender differences in amotivation, the consistent results across different cultural and educational settings add credibility to this trend. While the current study cannot determine the causal factors, this finding may reflect underlying sociocultural or educational dynamics within the Kuwaiti context. From an SDT perspective, it is possible that the educational environment differentially satisfies the psychological needs of male and female students. For instance, if certain academic tracks or pedagogical styles are perceived by male students as less autonomous or relevant to their future goals, this could thwart their needs and foster amotivation. This highlights a critical area for future qualitative research and for targeted institutional support aimed at enhancing male students' academic engagement. Overall, the evidence suggests a modest but strong gender effect, with males showing comparatively higher academic amotivation.

The current study shows that ChatGPT use significantly predicted academic amotivation among respondents, though the effect size was modest (R^2 = 0.041). The positive and statistically significant prediction (β = 0.202, p = .003) indicates that students who relied more on ChatGPT were more likely to experience higher levels of academic amotivation. This result is contrary to most of the existing evidence, which mostly points to motivational benefits linked to ChatGPT use. For example, Caratiquit & Caratiquit (2023) studied 178 Filipino students and found that using ChatGPT positively affected academic performance by increasing learning motivation. Likewise, Almulla (2024) reported that among 262

students at King Faisal University in Saudi Arabia, ChatGPT use boosted learning motivation and engagement. In Hong Kong, Lai et al. (2023) understudied 473 undergraduates and identified intrinsic motivation as the strongest factor influencing ChatGPT adoption. However, not all evidence supports this positive trend. Galindo-Domínguez et al. (2025) used data from 507 Spanish university students to directly examine amotivation in relation to ChatGPT use. They found a statistically significant positive relationship between the two ($p < 0.001$). This pattern mirrors what is observed in the present study. Self-Determination Theory (SDT) offers a valuable framework for interpreting this pattern. The relationship may reflect what can be described as an "optimization–substitution" tension. When students employ ChatGPT primarily as an answer-generating tool, i.e., when they substitute the AI's output for their own cognitive effort, it may inhibit the fulfillment of their basic psychological needs. By offloading the difficult but necessary cognitive work of synthesis and argumentation to the AI, students may bypass the very 'desirable difficulties' that build a sense of mastery. As a result, academic outcomes may feel unearned or detached from personal skill development, a hallmark of amotivation. In addition, habitual dependence on ChatGPT can diminish students' sense of ownership over the learning process, thereby undermining their need for autonomy. Collectively, these need-thwarting mechanisms offer a theoretically coherent explanation for why increased ChatGPT use may correspond with heightened academic amotivation. Overall, these findings suggest that while using ChatGPT can promote motivation and learning in some situations, excessive use or dependency may be connected to lower intrinsic engagement. The positive link between ChatGPT use and academic amotivation observed in this study highlights the need for a balanced, supervised approach to integrating generative AI tools in higher education.

7. Limitations

The data for this study was collected at a single point in time, which allows for the identification of correlations but prevents any causal inferences. In addition, the use of an author-developed ChatGPT Use Scale that has not yet undergone comprehensive psychometric validation. Although preliminary evidence of convergent validity was obtained through its correlation with the Perceived Importance of Technology scale, other forms of validity were not assessed. Future research should therefore subject this instrument to more rigorous validation procedures. Further, the sample was skewed towards female participants which limits the generalizability of findings related to gender. Finally, all data relied on self-report which may be subject to social desirability bias or inaccurate recall.

8. Recommendation

Implications for Educational Practice and Policy

The findings carry several implications for educational practice and policy in Kuwait and comparable contexts. First, institutions should consider strengthening critical AI literacy by offering training that emphasizes thoughtful, ethical and pedagogically productive use of generative AI. Ai needs to be positioned as a cognitive partner rather than a shortcut to final answers. Second, assessment designs may be updated to reduce opportunities for cognitive offloading, with greater emphasis on higher-order reasoning, creativity and personal reflection. Third, the higher levels of amotivation observed among male students highlight the need for targeted motivational interventions, including tailored advising, mentorship and programs that reinforce academic purpose and engagement. Finally, institutions should consider

developing clear guidelines on the appropriate use of generative AI to ensure consistent and responsible practices among students and faculty.

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10. เอกสารอ้างอิง (References)

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