AI AS A NEW ACADEMIC ALLY: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON STUDENTS' LEARNING HABITS

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ABSTRACT
This study investigates the adoption and usage of ChatGPT by college students in educational settings. The analysis uses a four-stage business analytics framework to look at usage, trust, confidence, motivation, acceptance, and verification patterns using survey data from 203 respondents in a variety of disciplines. The findings highlight ChatGPT's function as a tool for improving comprehension and self-assurance by demonstrating that the three strongest predictors of frequent use are understanding, trust, and confidence. The tension between critical evaluation and reliance on AI is highlighted by the fact that motivation plays a secondary role, and verification is largely irrelevant and negatively associated with trust. According to the research, generative AI works best when viewed as an academic ally that promotes learning and introspection rather than taking the place of critical thinking. The study

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provides context-bound findings that inform hypotheses for larger cross-institutional and cross-national research because of its single-country sample. The paper highlights recommendations to universities to foster AI literacy, safeguard the crucial academic integrity, and integrate ChatGPT into teaching practices responsibly and effectively.

Keywords: *Artificial Intelligence, ChatGPT, Learning habits, Business analytics, Higher education*

JEL classification: *C83, I21, M15*

1. INTRODUCTION

Higher education has quickly adopted artificial intelligence (AI), which is altering how students engage with course materials and approach homework. One of the most widely used tools is ChatGPT, a generative language model that can produce context-aware, human-like responses to open-ended questions. It is a helpful resource for students seeking explanations, summaries, or assignment assistance due to its adaptability and accessibility. Although ChatGPT and other AI tools have the potential to improve learning and foster academic independence, according to international research, they also highlight problems with misleading information, over-reliance, and ethical ambiguity. Students may benefit from increased productivity and better comprehension, but these advantages must be weighed against the potential for them to lose interest in critical thinking and self-directed learning. Furthermore, not much research has been done using primary data from local contexts, especially among undergraduate students in transitional education systems, despite growing interest in the global academic community.

In order to close that gap, this study examines how students use natural language processing (NLP) models such as ChatGPT, paying particular attention to important elements like usage frequency, motivation, understanding, trust, confidence, and verification of the information provided. Planning, using strategies, monitoring and verifying information, asking for help, and managing time are all examples of self-regulated, recurring study practices that we define as learning habits (Zimmerman, 1990; Verplanken and Orbell, 2003). The use of ChatGPT in these routines to scaffold comprehension and confidence while maintaining critical evaluation is referred to in this study as AI-mediated learning habits. The study employs a four-phase business analytics framework, i.e., prescriptive (producing strategic recommendations), diagnostic (analyzing underlying drivers), predictive (modeling usage patterns), and descriptive (identifying prevalent attitudes). Subsequently, we intend to provide a grounded perspective on how AI is changing learning strategies and expectations in higher education by surveying 203 students from a variety of academic programs in the Republic of North Macedonia.

The overall findings of this study show that a variety of cognitive, psychological, and behavioral factors influence college students' use of ChatGPT. Students primarily use ChatGPT to improve their understanding of difficult academic material and to boost their confidence in finishing assignments. These two constructs consistently show up as the strongest predictors of frequent usage. Additionally, trust is crucial because it mediates the link between behavioral engagement and cognitive gains, thereby strengthening adoption. On the other hand, motivation, while still important in early models, loses significance when confidence and trust are taken into account, suggesting that zeal by itself cannot support sustained use. Despite its academic value, verification has no discernible impact on adoption and even has a negative correlation with trust, indicating a latent conflict between critical analysis and AI dependence.

Strong relationships between trust, acceptance, understanding, and confidence are further revealed by correlation patterns, highlighting the fact that students use ChatGPT most successfully when they perceive both cognitive and affective benefits. When combined, these results imply that generative AI is more than just a handy tool; rather, it is an academic ally that enhances understanding and confidence, so long as its application is framed by ethical responsibility and critical engagement.

We systematize the paper in the following manner. In the following Section 2, we review some of the most notable global studies related to the topic that inspired the research. Section 3 presents the methodological approach, while in Sections 4 and 5 we present and discuss the obtained results based on the four main pillars of business analytics. Finally, we conclude the research in the last section.

2. LITERATURE REVIEW

Numerous studies have shown that artificial intelligence (AI) significantly affects students' motivation and involvement in academic activities. By offering individualized learning experiences that take into account each student's preferences and skills, artificial intelligence (AI) tools like learning analytics and intelligent tutoring systems have been demonstrated to increase student motivation and engagement (Elbadiansyah *et al*., 2024; Wadhwa *et al*., 2024). These resources enhance self-efficacy and problem-solving skills in addition to motivation, which improves academic performance (Jor, 2025). Through interactive and adaptive learning experiences, ChatGPT and other AI applications have been shown to dramatically increase student motivation and engagement in online learning environments, keeping students actively engaged in their studies (Rehman and Kang, 2024). Additionally, gamification components powered by AI add enjoyment and rewards to the educational process, which raises motivation and engagement even more (Wadhwa *et al*., 2024). AI integration in education is not without its difficulties, though. There are many worries about an over-reliance on AI, a decline in creativity, and moral dilemmas like justice and privacy (Elbadiansyah *et al*., 2024; Singh, 2024). Furthermore, concerns about academic dishonesty and how AI might affect teacher-student interactions need to be addressed (Jor, 2025). Nevertheless, if AI is applied carefully and morally, it can have significant positive effects on education overall, especially in raising student motivation and engagement (Singh, 2024; Jor, 2025).

Established technology-adoption frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) serve as the foundation for the integration of artificial intelligence (AI) into higher education. Prior to ChatGPT, early empirical research showed that students' willingness to interact with AI-driven learning environments is influenced by perceived utility, ease of use, and facilitating conditions (Strzelecki, 2023; Lin and Yu, 2023). These ideas are extended to large language models (LLMs) by Kasneci *et al*. (2023), who contend that explainability, transparency, and pedagogical alignment mediate acceptance. Along with emphasizing that AI tools co-construct learning practices rather than just automate cognitive tasks, theoretical perspectives also emphasize sociocultural and ethical lenses (Mhlanga, 2023). Since its public release, ChatGPT has rapidly spread across a variety of national contexts, according to survey-based investigations. More than 60% of Polish undergraduates had used ChatGPT within three months, mostly for brainstorming essays and summarizing readings, according to Strzelecki (2023). While confidence in disciplined use remained uneven across faculties, Chan and Hu (2023) also found high familiarity among Hong Kong students. Perceived comprehension gains and intrinsic learning motivation are strong predictors of sustained usage, according to multivariate analyses (Vieriu and Petrea, 2025). Notably, the effects of demographic moderators like gender and study level are inconsistent, indicating the need for more detailed, context-sensitive models (Lin and Yu, 2023). Evidence on learning effectiveness is emergent but promising. In controlled experiments, Chen and Gong (2025) demonstrated that compared to peers in a traditional workshop, international students who received writing feedback mediated by ChatGPT reported stronger self-regulation and significantly higher scores. Sykes's (2024) complementary findings show that AI-augmented critique tasks enhanced lexical richness and argumentative structure without reducing authorial voice. However, meta-analytic synthesis shows that effect sizes vary widely, and that learning gains are diminished when students lack critical prompting skills or when tasks emphasize rote knowledge (Kasneci *et al*., 2023).

Scholars document serious concerns about academic integrity in addition to the pedagogical benefits. Susnjak & McIntosh (2024) revived discussions on assessment design by proving that ChatGPT-generated responses can avoid human marking and traditional plagiarism detection. Extensive surveys reveal students' ambivalence: although the majority recognize efficiency gains, less than one-third regularly check the accuracy of facts (Strzelecki, 2023), reiterating concerns about taking AI results for granted. Universities are urged by regulatory and ethical analyses to create clear usage guidelines, encourage AI literacy, and foster critical data practices (Mhlanga, 2023).

We identify that there are three main conclusions drawn from the literature upon which we build our study: 1) students accept ChatGPT well, but only if it is conditioned by perceived cognitive value and ethical clarity; 2) well-scaffolded AI use can improve writing quality, conceptual understanding, and engagement; and 3) unmanaged reliance risks compromising integrity and eroding critical thinking. However, there are still unanswered questions about the socio-emotional aspects of AI-mediated research, disciplinary variations in prompt literacy, and long-term learning paths. To capture how changing LLM capabilities reshape higher-education ecosystems, future research should use intersectional lenses and longitudinal mixed-method designs. We found that understanding reflects perceived usefulness (TAM), trust reflects technology-trust beliefs, confidence reflects self-efficacy in self-regulated learning, motivation follows Self-Determination Theory, verification reflects metacognitive monitoring/need for cognition, and usage frequency reflects actual use (Davis, 1989; Zimmerman, 1990; Ryan and Deci, 2000). This contributes to the alignment of the established constructs in our study with the theoretical models developed.

3. METHODOLOGY

The research team created and distributed an anonymized online survey to find out how students feel about and behave when it comes to using artificial intelligence (AI) in classroom settings. Targeting university students from a wide range of academic programs, disciplines, and years of study, the survey tool was created using Google Forms. Convenience and snowball sampling methods were used for recruitment as well as peer networks. Because participation was voluntary and anonymous, a wide range of responses were guaranteed, social desirability bias was reduced, and ethical standards of research integrity were maintained. The analytical sample consisted of 203 valid responses in total. Eleven of the fifteen structured items on the questionnaire used a five-point Likert scale, with "strongly disagree" to "strongly agree" being the extremes. Students' perceived understanding of AI outputs, motivation to interact with AI, frequency of use, trust in AI systems, and inclination to verify information generated by AI were all measured by these items. To enable subgroup comparisons and the investigation of response heterogeneity, four demographic questions were also added, such as gender, age, academic field, and year of study. Internal consistency checks were performed on the survey items, which were drawn from well-established theoretical discussions on technology adoption and trust in digital systems in order to enhance construct validity. All things considered, the goal of this methodological approach was to match behavioral insights with measurable patterns so that recommendations based on empirical data could be developed to improve student engagement and direct institutional policies regarding the use of AI in higher education.

The four main phases of business analytics, descriptive, diagnostic, predictive, and prescriptive analysis, were followed when conducting the data analysis. First, descriptive statistics were used to find broad trends in the data and to summarize the demographic profile of the respondents. The linear relationships between important variables were then evaluated using correlation analysis, with particular focus on the interdependencies among motivation, comprehension, trust, and verification. This study used single-item indicators for key constructs, as mentioned, even though multi-item scales are typically better at capturing construct breadth and facilitating reliability estimates. The exploratory nature of the study and the requirement to reduce respondent burden in a student sample served as the basis for this decision. However, previous studies have shown that when constructs are concrete, unidimensional, and simple for respondents to understand, single-item measures can yield valid and reliable assessments. A single global job satisfaction item, for instance, showed acceptable validity and comparability with multi-item scales, according to Wanous *et al.* (1997). In the same manner, Bergkvist and Rossiter (2007) demonstrated that in applied contexts, single-item measures of attitude constructs can attain predictive validity comparable to multi-item scales. This method permits effective data collection and yields suggestive results that can be expanded in subsequent studies using validated multi-item scales, despite the notable trade-offs, which may lead to the inability to report internal consistency. Consequently, key perceptions were operationalized with single items because this was an exploratory survey limited by respondent burden. Since internal-consistency estimation and broader construct coverage are made possible by multi-item scales, we treat the results as indicative and broaden the study's limitations accordingly. Internal consistency metrics like Cronbach's alpha could not be reported because the constructs were measured using single items, and there was no test-retest data available. For concrete constructs, single-item measures may be justified; however, this method has limitations in terms of coverage and reliability. Furthermore, despite efforts to mitigate common-method bias through anonymity and neutral item wording, it still exists in all self-report surveys (Podsakoff *et al*., 2003).

After that, linear regression was used to apply predictive modeling, and the impact of explanatory variables on outcome measures was measured using Ordinary Least Squares (OLS) estimation. Lastly, the results were interpreted, and useful suggestions for integrating AI in academic settings were derived using what is usually considered prescriptive reasoning. For instance, the three-variate OLS regression described below was used to model the predictive relationship between the dependent variable (frequency of usage) and two explanatory factors, namely motivation and understanding:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i$$

where with Y_i we denote the dependent variable, i.e., the trust level of respondents (i), with X_{1i} and X_{2i} we denote the independent variables – motivation and understanding, respectively. The intercept is denoted with $,\beta_0,$ while the slope coefficients for each of the two independent variables with β_1 and β_2. Finally, the error term (ε_i) is assumed to satisfy the Gauss-Markov conditions.

4. ANALYSIS AND RESULTS

4.1. Descriptive analysis

We used descriptive statistics in the first stage of the analysis to get a general idea of how students felt and behaved with regard to ChatGPT. To determine prevailing patterns and participant consensus, measures of central tendency, variability, and the shape of the distribution were computed for every Likert-scale question. Depending on the context of the construct, we label *"Using ChatGPT increases my self-confidence when completing academic tasks"* as a construct variable for confidence, *„Before using information obtained from ChatGPT, I check the accuracy through other sources (e.g. textbook, Google Scholar)"* as a construct for verification, *„ChatGPT helps me understand complex academic material"* for understanding, *„ Using ChatGPT increases my motivation to study independently (without help from other people)"* as a construct for motivation, and *„I fully trust the answers without verification"* as a construct for observing trust. Subsequently, we mainly focus on these four constructs later in the study.

Students see ChatGPT as a useful tool for improving their academic comprehension, as evidenced by the high mean score of 4.06 for the item *"ChatGPT helps me understand complex academic material."* Furthermore, a perceived psychological advantage is indicated by the statement, *"Using ChatGPT increases my self-confidence when completing academic tasks"* ($\mu = 3.59$). Lower scores, however, for statements like *"I fully trust the answers without verification"* ($\mu = 3.21$), indicate that students should approach AI-generated content critically and cautiously. The detailed descriptive statistics are presented in Table 1.

In the end, the descriptive analysis reveals a balanced user mindset, where students are aware of ChatGPT's limitations and the need for additional testing and development, but they are also willing to use it for academic purposes. These findings set the stage for a more in-depth investigation of how and why students engage in specific behaviors in the subsequent stages of analysis. Instead of passively accepting ChatGPT's outcomes, students use it primarily critically and constructively, as evidenced by the distributions' shape and variability. The majority of constructs show moderate negative skewness, indicating a tendency to concur with claims regarding self-directed use and critical evaluation. The overall pattern suggests that users will continue to use ChatGPT as a tool to improve understanding and independence while exercising caution and using its products sparingly.

Table 1: Descriptive statistics of the Likert-scaled constructs.

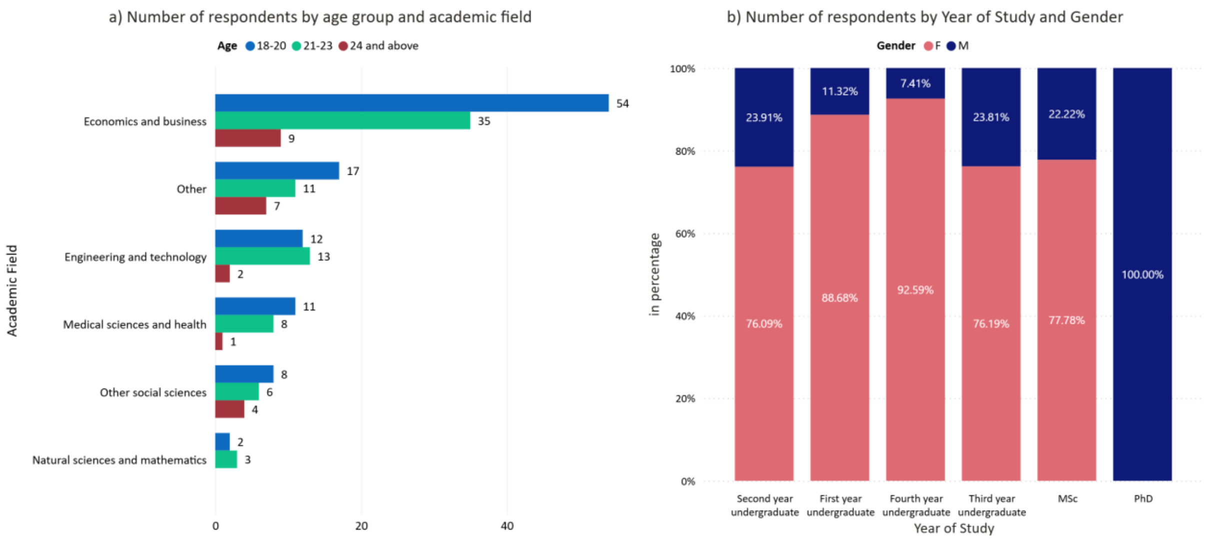
Construct	μ	**St. Error**	Me	Mo	σ	σ^2	**Excess Kurtosis**	**Skewness**
„I fully trust the answers without verification"	3.241	0.077	3	3	1.093	1.194	-0.277	-0.309
„Before using information obtained from ChatGPT, I check the accuracy through other sources (e.g., textbook, Google Scholar)"	3.212	0.095	3	4	1.357	1.841	-1.130	-0.247
"Using ChatGPT increases my self-confidence when completing academic tasks"	3.586	0.080	4	3	1.142	1.303	-0.252	-0.567
„ChatGPT helps me understand complex academic material"	4.064	0.080	4	5	1.135	1.288	0.983	-1.276

„After using ChatGPT, I am less likely to ask for additional help from colleagues or professors"	3.655	0.087	4	5	1.239	1.534	-0.326	-0.724
„Using ChatGPT increases my motivation to study independently (without help from other people)"	3.512	0.094	4	5	1.340	1.796	-0.861	-0.525

(Source: Authors' calculations ($n = 203$))

Most of the respondents sampled are second year undergraduate studies (92), followed by first year undergraduates (53), fourth (27), and third year (21). The distribution across academic fields, age, and gender shows that most of them (consistently above 75% in first and second cycle studies) are female and enrolled in the field of economics and business (see Figure 1). Approximately 89% of respondents are aged between 18 and 23, with the first group aged 18-20 contributing to 51.2% of the entire sample.

Figure 1a and 1b: Demographics of the sampled respondents.



(Source: Authors' calculations ($n = 203$))

4.2. Diagnostic analysis

In the diagnostic phase, we applied correlation analysis to examine relationships between key academic variables. The correlation heatmap in Figure 2 offers a deeper comprehension of how students' attitudes, behaviors, and perceptions interact with regard to using ChatGPT for academic purposes. A complex picture of how cognitive, motivational, and affective constructs influence engagement with generative AI is provided by the numerous strong and moderately positive correlations that show up along with a few weak or negative associations. First, Frequency of Usage is strongly associated with Understanding ($r = 0.556$) and Confidence ($r = 0.574$), with Trust ($r = 0.468$) coming in second. This trend suggests that when students feel confident in their academic skills while using ChatGPT and believe it to be a tool that improves comprehension, they are more likely to use it regularly. Although its impact is less pronounced than that of confidence and understanding, trust serves to further reinforce this tendency. Additionally, motivation and usage have a positive correlation ($r = 0.437$), indicating that willingness to learn on one's own increases use frequency, albeit as a secondary driver. Verification, on the other hand, has a negative correlation with frequency ($r = -0.104$), suggesting that students who routinely verify ChatGPT's responses use it less frequently.

Second, when looking at inter-construct relationships, we find that Trust and Acceptance have a strong correlation ($r = 0.616$), meaning that students who are more likely to accept ChatGPT's outputs also have higher levels of confidence in its dependability. Additionally, there is a strong correlation between trust and understanding ($r = 0.514$) and confidence ($r = 0.537$), highlighting the role that self-assurance and cognitive gains play in the development of tool confidence. Interestingly, motivation has strong positive relationships with both understanding ($r = 0.603$) and confidence ($r = 0.696$), indicating that motivated learners are more likely to feel competent and perceive cognitive benefits when using ChatGPT. Third, the counter-factor that always sticks out is verification. It has a weak negative correlation with Understanding ($r = -0.092$), Motivation ($r = -0.079$), Acceptance ($r = -0.216$), and Trust ($r = -0.305$). This highlights a possible conflict: students who place a strong emphasis on verification might continue to have doubts about ChatGPT, which would reduce acceptance and trust. In this context, critical evaluation seems to lessen habitual reliance on AI tools, even though it is desirable academically. These findings point to three key positive predictors that together propel ChatGPT's incorporation into students' daily learning routines: trust, understanding, and confidence. While verification creates friction by reducing reliance and trust, motivation indirectly reinforces these dynamics.

Figure 2: Heatmap of correlation coefficients.

(Source: Authors' calculations ($n = 203$))

4.3. Predictive analysis

To determine which factors most significantly influence the frequency of ChatGPT usage among students, a multiple linear regression analysis was conducted. The dependent variable was self-reported usage frequency, measured on a five-point Likert scale, while the independent variables were perceived understanding of academic material, motivation for independent learning, trust in the content provided by ChatGPT, the need for verification of output, and the perceived individual confidence in learning without additional help from professors and peers. To better understand what influences the frequency of ChatGPT use for academic purposes, the regression analysis was organized into four nested models, each of which progressively added more explanatory variables. Students' self-reported frequency of use served as the dependent variable, and all constructs were scored on a five-point Likert scale.

Two initial core factors - understanding and motivation were included in Model 1 (see Table 2). With a β_1 of 0.4550, the results unmistakably showed that understanding was the primary factor driving adoption among students. This suggests that with each small increase in perceived understanding, students who believe ChatGPT to be a useful tool for improving comprehension use it much more frequently. Despite being positive and significant ($\beta_2 = 0.1333$), motivation had a less pronounced effect, suggesting that it plays a supporting role in adoption. About one-third of the variation in usage can be explained by these two psychological constructs, according to the coefficient of determination of 0.3252 and adjusted $R^2$of 0.3185. This can be considered a significant share for behavioral research that uses perceptual scales.

The explanatory landscape changed with the introduction of the factor Trust in Model 2. Students who have a higher trust in ChatGPT are significantly more likely to use it regularly, as indicated by the coefficient for trust, which was 0.2315. Simultaneously, the Understanding (0.4373) and Motivation (0.0870) coefficients showed a slight decrease, indicating that the trust dimension may mediate or overlap with their effect overall. With R^2 increasing to 0.3606, the model's explanatory power increased, indicating that the inclusion of trust improves the regression's predictive ability and captures significant relational aspects of AI engagement.

In response to students' propensity to double-check ChatGPT's responses, Model 3 added Verification to its specification. However, the verification coefficient ($\beta_4 = 0.0076$) is statistically insignificant and negligible, indicating that students' frequency of use of ChatGPT is not systematically impacted by their fact-checking practices. This may indicate that students in fact use it independently of the quality of information provided, creating knowledge distortion and bias. Crucially, motivation stayed low (0.0866), but understanding (0.3728) and trust (0.2349) continued to have significant and favorable effects. The adjusted R^2 of 0.3478 demonstrated minimal improvement over the prior model, highlighting the low contribution of verification to adoption frequency explanation.

Finally, Model 4 introduced Confidence, which is characterized as students' self-assurance when using ChatGPT to complete academic assignments. The dynamics of the model were significantly changed by its inclusion. Confidence showed a strong slope coefficient β_5 of 0.3139, indicating that students use ChatGPT much more frequently after they feel competent and empowered to produce quality academic work. In contrast, Motivation completely lost significance (and changing the sign of impact to -0.0216), while Understanding (0.2629) and Trust (0.1755) continued to have positive effects, albeit with somewhat diminished effects when compared to previous models. Once more, which was desirable to confirm the previously set thesis, verification had no statistically distinct impact (-0.0027). Verification again had no meaningful effect (-0.0027). The explanatory power of the model increased further, with adjusted R^2 to 0.3849, meaning that the full set of predictors accounts for approximately 40% of the variation in ChatGPT usage, which is a considerable share for behavioral models in social science research. An important realization is demonstrated by the models' progressive increase in explanatory power, where although cognitive factors (understanding) serve as the foundation for adoption, relational (trust) and psychological (confidence) variables significantly enhance the explanatory framework. Although motivation is important at first, it becomes unnecessary when trust and confidence are taken into account. This suggests that students' perceived competence and confidence in their ability to use AI effectively are more important than intrinsic drive. While students may verify information, this behavior does not systematically determine adoption levels. In contrast, verification is consistently irrelevant in predicting the frequency of use. The results highlight that regular and intentional use of ChatGPT for academic purposes for students is based on a so-called triad of understanding, trust, and confidence rather than being merely motivated by enthusiasm or habit. These findings note the significance of instructional approaches that develop an understanding of AI's advantages and disadvantages, establish confidence in its proper use, and, moreover, encourage students to incorporate AI into their daily academic routines.

Table 2: Regression model

Variable	Model 1	Model 2	Model 3	Model 4
Constant	1.2147^{***} (0.2453) [4.9521]	0.9589^{***} (0.2515) [3.8131]	0.9272^{***} (0.3263) [2.8417]	0.8535^{***} (0.3175) [2.6879]
Understanding	0.4550^{***} (0.0720) [6.3163]	0.4373^{***} (0.0745) [5.0121]	0.3728^{***} (0.0748) [4.9862]	0.2629^{***} (0.0788) [3.3386]
Motivation	0.1333^{**} (0.0610) [2.1839]	0.0870 (0.0612) [1.4227]	0.0866 (0.0614) [1.4114]	-0.0216 (0.0667) [-0.2336]
Trust		0.2315^{***} (0.0697) [3.3189]	0.2349^{***} (0.0734) [3.2014]	0.1755^{**} (0.0731) [2.3996]
Verification			0.0076 (0.0496) [0.1529]	-0.0027 (0.0482) [-0.0555]
Confidence				0.3139^{***} (0.0872) [3.5933]
AIC	2.7003	2.6563	2.6660	2.6122
R^2	0.3252	0.3606	0.3607	0.4002
Adj. R^2	0.3185	0.3510	0.3478	0.3849
St. Error	0.9267	0.9043	0.9066	0.8804
Obs.	203	203	203	203

Note: ***, **, and * indicate 1%, 5%, and 10% statistical significance, respectively.

(Source: Authors' calculations)

5. PRESCRIPTIVE ANALYSIS AND DISCUSSION

A dual imperative for higher education is highlighted by the integration of diagnostic and predictive results, i.e., to minimize the risks of uncritical dependence while utilizing the cognitive and motivational advantages of generative AI. According to the correlation analysis, usage frequency is most strongly associated with understanding and confidence, then with trust. This implies that students use ChatGPT not just for convenience but also because it improves understanding and increases confidence in finishing assignments. This finding was supported by regression models, which showed that the three most reliable indicators of continued use were understanding, trust, and confidence. When confidence and trust were taken into account, motivation's explanatory power diminished, indicating that intrinsic drive is eventually absorbed into larger cognitive and psychological processes. On the other hand, acceptance showed up in correlations as being closely associated with trust but lacking independent predictive power, whereas verification consistently failed to predict usage. This pattern has significant implications. First and foremost, ChatGPT ought to be purposefully positioned as an aid for understanding and empowerment rather than as a substitute for human intellect. The students who integrate ChatGPT into their learning routines the most frequently are those who see cognitive gains and have faith in their ability to use it successfully. This supports the idea that AI tools actively contribute to students' sense of competence rather than acting as neutral accessories. Therefore, the goal of educational design must be to embed self-regulation and reflection while also scaffolding the use of AI in ways that improve understanding.

The conflict between verification and trust necessitates careful pedagogical consideration. According to correlation results, students who have greater faith in ChatGPT are more likely to verify less, increasing their exposure to false or misleading information. This paradox highlights a larger issue with AI literacy, for instance that skepticism can be undermined by the same confidence that keeps usage going. Verification must become a standard academic practice at universities rather than a self-made choice. Moreover, it can be turned from a usage deterrent into an essential intellectual discipline through structured assignments in which students annotate, critique, or cross-reference ChatGPT's outputs with reliable sources. By doing so, critical engagement could be reframed as an asset rather than a threat to confidence. In order to position ChatGPT as a catalyst for exploration, instructional design needs to change to incorporate hybrid learning strategies. For instance, in flipped classroom settings, students may utilize ChatGPT before lectures to produce draft arguments or explanations that can subsequently be discussed with peers and verified with teachers. AI becomes more of a conversation starter and an exploratory scaffold in this situation rather than a content provider. In a similar manner, gamified or group projects where ChatGPT facilitates brainstorming can connect motivation to creative and interactive use as opposed to rote dependence. These kinds of designs encourage criticism, innovation, and discussion - exactly the traits that guard against over-reliance.

In the end, the results broaden current discussions about academic integrity and digital ethics. Verification's feeble and frequently detrimental function highlights how important standards could be undermined if AI adoption is not controlled. A generation of students who delegate judgment to machines could be fostered in the absence of clear boundaries. Prescriptive tactics must be used in classrooms and institutions to combat this. Universities should establish clear usage guidelines, offer specific instruction in AI literacy, and uphold intellectual integrity standards. Simultaneously, educators need to establish learning environments that value skepticism, independent judgment, and fact-checking as essential academic qualities. As demonstrated by their frequent editing of ChatGPT's outputs, students already demonstrate encouraging instincts for critical engagement, however, in order to avoid complacency, these instincts need to be systematically reinforced.

This study has a number of limitations despite its contributions. Because students may overestimate their understanding or underestimate their reliance on ChatGPT, the use of self-reported survey data raises the possibility of what is called a response bias. Although the sample spans several faculties, it is limited to a single country, which restricts how broadly the results can be applied in global terms. External validity is limited because the study is deemed exploratory, utilizing a convenience sample that is primarily made up of young, female undergraduates studying business and economics in a single national higher education system. To reduce respondent burden, all focal constructs were measured using single items, which may have resulted in lower construct coverage and prevented internal-consistency estimation. Additionally, although a number of predictors were taken into account, important dimensions may have been overlooked because other variables like prior AI exposure, digital literacy, and disciplinary differences were left out. Last but not least, the cross-sectional design records student behavior at a specific moment in time, making it impossible to draw conclusions about causality or track changing practices. In order to overcome these constraints, future studies should use longitudinal designs that monitor how AI use changes over time, particularly as generative technologies and educational pressures change. Predictive models and interpretations could be improved by adding more variables, such as prompt engineering abilities, field of study, or AI literacy levels. By using validated multi-item scales that can yield more robust construct validity and reliability estimates, future research should build on this exploratory work. Key dimensions are more thoroughly covered by well-established metrics like computer self-efficacy (Compeau and Higgins, 1995), trust in technology constructs (McKnight *et al.*, 2002), and perceived usefulness and ease of use from the TAM - Technology Acceptance Model (Davis, 1989). Similarly, the conceptual precision of concepts like motivation, verification, and learning regulation could be expanded through the incorporation of motivational frameworks from Self-Determination Theory (Ryan and Deci, 2000) and the Need for Cognition Scale (Cacioppo and Petty, 1982). Future research can improve robustness, facilitate cross-study comparability, and offer more profound understandings of how AI tools alter students' learning patterns by utilizing these tools. Furthermore, in addition to the quantitative insights provided here, experimental and mixed-method approaches may uncover the causal mechanisms relating to confidence, verification, and trust. In addition to expanding theoretical knowledge, this kind of research would give academic institutions more useful advice on how to strike a balance between academic integrity and technological efficiency.

6. CONCLUSION

By providing empirical insights into how university students adopt and use ChatGPT for academic purposes, this study adds to the growing body of research on the role of generative artificial intelligence in higher education. Based on a sample of 203 respondents from various academic fields and levels, the analysis revealed a complex interaction between behavioral, affective, and cognitive factors that support usage patterns. The findings show that students are not merely adopting ChatGPT out of novelty or convenience; rather, their engagement is strongly anchored in perceived understanding, relational trust, and self-confidence. These three constructs, which together might be referred to as the “triad of adoption,” have continuously been found to be the most significant motivators of frequent use. Although motivation was important at first, it lost its explanatory power when confidence and trust were added, demonstrating that zeal by itself cannot support sustained use. Verification, on the other hand, although academically desirable, was found to be largely irrelevant as a predictor of adoption and even showed negative associations with trust, indicating that students who regularly fact-check are less likely to use ChatGPT.

When put together, these findings provide a complex picture of the use of AI in educational settings. Although the data shows a latent risk of overconfidence and diminished verification, students seem to be willing to use ChatGPT critically and constructively, editing its outputs and using it as a learning tool. In order to prepare students to strike a balance between confidence and skepticism, higher education institutions must actively incorporate AI-critical literacy into their curricula. Instead of discouraging use, educational approaches that promote annotation, cross-referencing, and triangulation of AI-generated outputs may turn verification into a deeply ingrained academic practice. Additionally, ChatGPT can be made to act as a catalyst for inquiry, contemplation, and discussion rather than a passive answer engine by implementing hybrid pedagogical models like flipped classrooms, gamified projects, or group projects.

Additionally, the study adds to larger discussions about academic integrity and digital ethics. Overregulation may limit the innovative potential of these tools, while an unrestrained reliance on generative AI runs the risk of weakening critical thinking and encouraging complacency in fact-checking. Therefore, the challenge is to create classroom procedures and institutional policies that uphold strict standards of truth, accuracy, and independent thought while acknowledging AI as a valid academic ally. According to the concluding evidence, how educational institutions mold students' perceptions, trust, and confidence in using these tools responsibly will determine the future of AI in education rather than just technological capabilities. ChatGPT and related systems can improve understanding, empower students, and eventually promote a culture of thoughtful and responsible AI integration if they are backed by ethical standards, critical literacy initiatives, and innovative teaching practices.

REFERENCES

Bergkvist, L. and Rossiter, J.R. (2007), "The predictive validity of multiple-item versus single-item measures of the same constructs", *Journal of Marketing Research*, Vol. 44 No. 2, pp. 175-184.

Cacioppo, J.T. and Petty, R.E. (1982), "The need for cognition", *Journal of Personality and Social Psychology*, Vol. 42 No. 1, pp. 116-131.

Chan, C.K.Y. and Hu, W. (2023), "Students' voices on generative AI: perceptions, benefits, and challenges in higher education", *International Journal of Educational Technology in Higher Education*, Vol. 20 No. 1, p. 43.

Chen, C. and Gong, Y. (Frank) (2025), "The role of AI-assisted learning in academic writing: a mixed-methods study on Chinese as a second language students", *Education Sciences*, Vol. 15 No. 2, p. 141.

Compeau, D.R. and Higgins, C.A. (1995), "Computer self-efficacy: development of a measure and initial test", *MIS Quarterly*, Vol. 19 No. 2, pp. 189-211.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340.

Elbadiansyah, Sain, Z.H., Shehu Lawal, U., Chansa Thelma, C. and Luqman Aziz, A. (2024), "Exploring the role of artificial intelligence in enhancing student motivation and cognitive development in higher education", *TechComp Innovations: Journal of Computer Science and Technology*, Vol. 1 No. 2, pp. 59-67.

Jor, J. (2025), "Impact of artificial intelligence on engagement, motivation, work efficiency, and academic outcomes", in Barstow, C. and Briel, H. (Eds.), *Connecting Ideas, Cultures, and Communities*, 1st ed., Routledge, London, pp. 511-515.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Kuhn, J. and Kasneci, G. (2023), "ChatGPT for good? On opportunities and challenges of large language models for education", *Learning and Individual Differences*, Vol. 103, 102274.

Lin, Y. and Yu, Z. (2024), "A bibliometric analysis of artificial intelligence chatbots in educational contexts", *Interactive Technology and Smart Education*, Vol. 21 No. 2, pp. 189-213.

McKnight, D.H., Choudhury, V. and Kacmar, C. (2002), "Developing and validating trust measures for e-commerce: an integrative typology", *Information Systems Research*, Vol. 13 No. 3, pp. 334-359.

Mhlanga, D. (2023), "Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning", *SSRN Electronic Journal*, [Preprint].

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.

Rehman, N. and Kang, M.A. (2024), "Exploring the impact of artificial intelligence on students' engagement and motivation in online learning environments", *International Journal of Trends and Innovations in Business & Social Sciences*, Vol. 2 No. 4.

Ryan, R.M. and Deci, E.L. (2000), "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being", *American Psychologist*, Vol. 55 No. 1, pp. 68-78.

Singh, P. (2024), "Artificial intelligence and student engagement: drivers and consequences", in Gierhart, A.R. (Ed.), *Advances in Educational Technologies and Instructional Design*, IGI Global, pp. 201-232.

Strzelecki, A. (2024), "To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology", *Interactive Learning Environments*, Vol. 32 No. 9, pp. 5142-5155.

Susnjak, T. and McIntosh, T. (2024), "ChatGPT: the end of online exam integrity?", *Education Sciences*, Vol. 14 No. 6, p. 656.

Sykes, E.R. (2024), "AI-assisted academic writing: a comparative study of student-crafted and ChatGPT-enhanced critiques in ubiquitous computing", *International Journal of Advanced Computer Science and Applications*, Vol. 15 No. 9.

Verplanken, B. and Orbell, S. (2003), "Reflections on past behavior: a self-report index of habit strength", *Journal of Applied Social Psychology*, Vol. 33 No. 6, pp. 1313-1330.

Vieriu, A.M. and Petrea, G. (2025), "The impact of artificial intelligence (AI) on students' academic development", *Education Sciences*, Vol. 15 No. 3, p. 343.

Wadhwa, R., Rabby, F., Bansal, R. and Hundekari, S. (2024), "Drivers and impact of artificial intelligence on student engagement", in Bansal, R., Chakir, A., Hafaz Ngah, A., Rabby, F. and Jain, A. (Eds.), *Advances in Computational Intelligence and Robotics*, IGI Global, pp. 161-170.

Wanous, J.P., Reichers, A.E. and Hudy, M.J. (1997), "Overall job satisfaction: how good are single-item measures?", *Journal of Applied Psychology*, Vol. 82 No. 2, pp. 247-252.

Zimmerman, B.J. (1990), "Self-regulated learning and academic achievement: an overview", *Educational Psychologist*, Vol. 25 No. 1, pp. 3-17.