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FACTORS INFLUENCING CHATGPT USAGE AMONG UNIVERSITY STUDENTS: AN EMPIRICAL STUDY IN GEORGIA

Abstract. This study investigates the key determinants influencing the adoption of ChatGPT among university students in Georgia, contributing to the growing body of literature on artificial intelligence integration in higher education. As generative AI tools become increasingly prevalent in academic environments worldwide, understanding the factors that drive or inhibit their adoption in specific socio-cultural and institutional contexts is of critical importance. This research addresses a notable gap in the existing scholarship, as post-Soviet educational settings remain significantly underrepresented in technology adoption studies despite their distinct structural and cultural characteristics.

The study draws on primary data collected from 150 students enrolled at a Georgian university through an online questionnaire utilizing a 10-point Likert scale. Logistic regression analysis was applied to identify statistically significant predictors of ChatGPT usage for academic purposes. The analytical framework integrates social influence theory with established technology acceptance models, offering a theoretically grounded lens through which to interpret adoption behavior in the context of generative AI tools.

The findings reveal that peer encouragement and institutional support are the most influential factors driving ChatGPT adoption, with odds ratios of 1.180 and 1.264, respectively. These results underscore the pivotal role that social networks and university-level policies play in shaping students' willingness to incorporate AI tools into their academic workflows. Strong positive correlations were also identified between perceived helpfulness in completing assignments, improved comprehension of complex subject matter, and overall study efficiency, suggesting that students are primarily motivated by tangible academic benefits when evaluating AI tools.

Gender differences in adoption patterns were examined, with male students demonstrating a statistically significant higher likelihood of using ChatGPT for academic work compared to their female counterparts. This finding highlights the importance of considering demographic variables when designing AI literacy programs and institutional support structures.

The study further evaluates the tension between fostering technological innovation and upholding academic integrity within higher education institutions. As universities navigate the challenges posed by generative AI, the findings provide actionable implications for the development of evidence-based AI integration strategies. This research ultimately calls for a balanced institutional approach, one that promotes digital competency and equitable access while safeguarding the principles of original scholarly work.

Keywords: ChatGPT, Artificial Intelligence in Education, Technology Acceptance, Peer Influence, University Support.

JEL Classification: I21; I23; O33; C25; D83.

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Introduction. The rapid advancement of artificial intelligence technologies has fundamentally transformed numerous aspects of contemporary society, with the education sector experiencing particularly profound changes. The emergence of ChatGPT in November 2022 marked a watershed moment in the accessibility of sophisticated natural language processing tools, creating both opportunities and challenges for educational institutions worldwide. Within months of its release, ChatGPT garnered unprecedented attention from students, educators, and policymakers, prompting urgent discussions about the role of AI in academic settings. University students have emerged as primary adopters of ChatGPT, integrating this technology into various aspects of their academic work, from research assistance to assignment completion. The tool's ability to generate human-like text, explain complex concepts, and provide instant feedback on diverse topics has made it particularly attractive to students facing increasing academic pressures. However, this rapid adoption has occurred largely without systematic understanding of the underlying motivations and factors driving student behavior. While some students embrace ChatGPT as a valuable learning aid that enhances their educational experience, others express concerns about academic integrity, the potential for plagiarism, and overreliance on AI-generated content.

The Georgian higher education context presents a particularly interesting case for examining ChatGPT adoption. As a country transitioning from a post-Soviet educational model toward European standards, Georgian universities face unique challenges in integrating emerging technologies while maintaining academic rigor. The limited research on AI tool adoption in Georgian educational settings creates a significant knowledge gap, particularly regarding how cultural, institutional, and social factors influence technology acceptance among students. This study addresses this gap by investigating the primary determinants of ChatGPT usage among Georgian university students. We focus specifically on identifying which factors most significantly predict whether students will adopt ChatGPT for academic purposes. Understanding these factors is essential for several stakeholders. Universities need evidence-based insights to develop appropriate policies that neither stifle innovation nor compromise academic standards. Educators require knowledge about student technology use patterns to adapt their teaching methods effectively. Policymakers must understand the implications of AI adoption for educational quality and equity. Furthermore, students themselves benefit from clear guidance on responsible AI tool usage.

The object of the research is the process of ChatGPT adoption in the context of Georgian higher education. The subject of the research is the complex of social, institutional, and individual factors, including peer influence, institutional support, perceived usefulness, and digital literacy, that shape students' decisions to incorporate ChatGPT into their academic activities.

The aim of the study is to identify and empirically assess the key determinants of ChatGPT adoption among university students in Georgia, and to establish an evidence-based understanding of how social and institutional conditions shape technology acceptance in a post-Soviet educational environment.

To achieve this aim, the following tasks were formulated. First, to review the existing theoretical frameworks on technology acceptance and social influence and evaluate their applicability to generative AI tools in educational contexts. Second, to examine the socio-demographic and behavioral profiles of ChatGPT users among Georgian university students. Third, to assess the effects of peer influence and institutional support on students' adoption decisions. Fourth, to analyze the relationships between perceived usefulness, digital literacy, and actual patterns of ChatGPT usage. Fifth, to investigate gender-based differences in adoption behavior. Sixth, to provide practical recommendations for universities and policymakers regarding the design of AI integration strategies in higher education.

The research addresses the following key questions: What are the primary factors that motivate students to use ChatGPT for academic work? How do peer influence and institutional support affect adoption decisions? What relationships exist between perceived usefulness, ease of use, and actual usage patterns? How do demographic characteristics influence ChatGPT adoption among students?

The study makes several important contributions to existing literature. First, it provides empirical evidence from a previously understudied geographic context, expanding our understanding of technology adoption beyond Western educational settings. Second, it applies established theoretical frameworks from technology acceptance research to the emerging context of generative AI tools, testing their validity in this new domain. Third, it offers practical insights for educational administrators developing policies around AI tool usage. Finally, it establishes a baseline understanding of student AI adoption patterns that can inform future longitudinal research tracking how these patterns evolve. The timing of this research is particularly significant as universities worldwide grapple with formulating appropriate responses to ChatGPT and similar technologies. Some institutions have moved toward restrictive policies or outright bans, while others have embraced these tools as legitimate educational aids. This study contributes to more nuanced, evidence-based policy development by identifying the specific factors that drive student adoption, allowing institutions to design interventions that address root causes rather than merely restricting access.

Literature Review. The theoretical foundation for understanding ChatGPT adoption among students draws from multiple research streams, including technology acceptance models, social influence theory, and studies specific to AI in educational contexts. This section synthesizes recent scholarly work to establish the conceptual framework guiding our empirical investigation. The Technology Acceptance Model (TAM), originally developed by Davis (1989) and subsequently refined by numerous researchers, provides the foundational theoretical lens for examining ChatGPT adoption. TAM posits that perceived usefulness and perceived ease of use are primary determinants of technology acceptance and usage behavior. Venkatesh and Davis (2000) extended this model to include social influence processes, demonstrating that subjective norms and voluntary nature significantly affect technology adoption decisions. More recent adaptations of TAM have successfully explained adoption of various educational technologies, from learning management systems to mobile learning applications (Abdullah & Ward, 2016; Scherer et al., 2019). Research on artificial intelligence in education has expanded significantly in recent years, though studies specifically examining ChatGPT remain relatively limited due to the tool's recent emergence. Kasneci et al. (2023) provide a comprehensive analysis of ChatGPT's potential applications in education, highlighting both opportunities for personalized learning and risks related to academic integrity. They argue that ChatGPT represents a paradigm shift requiring fundamental reconsideration of assessment methods and learning objectives. Similarly, Rudolph et al. (2023) examine ChatGPT through the lens of educational innovation, suggesting that resistance to AI tools may prove futile and that educators should instead focus on productive integration strategies. Peer influence emerges as a critical factor in technology adoption across multiple contexts. Social influence theory, articulated by Kelman (1958) and expanded by contemporary researchers, suggests that individuals adopt behaviors and technologies partly based on their social networks' actions and recommendations. In educational settings, peer effects have demonstrated particular strength, with students often relying on classmates' experiences when evaluating new learning tools (Salanova et al., 2005; Tarhini et al., 2017). Recent research by Dwivedi et al. (2023) specifically examined social factors in ChatGPT adoption, finding that word-of-mouth recommendations and peer usage patterns significantly influenced individual adoption decisions.

Institutional support and organizational context play equally important roles in technology acceptance. Rogers' (2003) diffusion of innovation theory emphasizes that organizational characteristics, including support structures and resource availability, affect innovation adoption rates. In educational settings, institutional support manifests through various mechanisms: technical infrastructure, training programs, policy frameworks, and explicit endorsement from administrators (Hew & Brush, 2007; Sumak et al., 2011). Research by Trust et al. (2023) demonstrates that universities providing clear guidance and support for AI tool usage experience higher adoption rates and more productive integration compared to institutions maintaining ambiguous or restrictive policies. The relationship between perceived usefulness and technology adoption has received extensive empirical validation across contexts. In educational technology research, students consistently demonstrate higher adoption rates for tools they perceive as directly beneficial to their academic performance (Mohammadi, 2015; Teo & Noyes, 2011). Recent studies examining ChatGPT specifically have found that students who perceive the tool as helpful for completing assignments and understanding difficult concepts show significantly higher usage rates (Baidoo-Anu & Owusu Ansah, 2023; Chan & Hu, 2023). However, these relationships may be moderated by concerns about academic integrity and learning authenticity.

Digital literacy and technological confidence represent additional important considerations. Van Deursen and Van Dijk (2014) distinguish between operational, formal, information, and strategic digital skills, arguing that higher-order skills particularly influence effective technology use. Students with greater technological confidence demonstrate more willingness to experiment with new tools and overcome

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initial difficulties (Hatlevik et al., 2018). For ChatGPT specifically, comfort with AI interfaces and understanding of prompt engineering may differentiate successful users from those who struggle to derive value from the tool (Mollick & Mollick, 2023).

Academic pressure and workload considerations influence students' decisions to adopt productivity-enhancing technologies. Time pressure theory suggests that individuals facing high demands seek efficiency-improving tools (Maruping & Magni, 2015). Several researchers have documented that students experiencing heavy academic workloads demonstrate higher adoption rates for tools promising time savings or efficiency gains (Nistor et al., 2014; Park, 2009). ChatGPT's ability to rapidly generate drafts, summaries, and explanations may prove particularly attractive to time-constrained students, though this same feature raises concerns about superficial learning and academic dishonesty (Cotton et al., 2023). Ethical concerns and academic integrity considerations present potentially countervailing forces to adoption. Research on academic dishonesty has long established that students balance perceived benefits against moral considerations and detection risks (McCabe et al., 2012; Tindall & Curtis, 2020). For ChatGPT, the ethical landscape remains particularly murky, with universities often providing unclear or conflicting guidance about appropriate use boundaries (Sullivan et al., 2023). Studies examining student attitudes reveal considerable confusion about what constitutes legitimate versus inappropriate ChatGPT usage, with many students uncertain whether using AI assistance represents a form of academic misconduct (Perkins, 2023; Tlili et al., 2023).

Gender differences in technology adoption have produced mixed findings across contexts. Some research suggests males demonstrate higher adoption rates for novel technologies and greater comfort with technical tools (Venkatesh & Morris, 2000), while other studies find these differences diminishing or reversing in specific contexts (Cai et al., 2017). For ChatGPT specifically, preliminary evidence suggests gender may influence both adoption rates and usage patterns, though the mechanisms remain unclear (Kooli, 2023). The limited research on ChatGPT adoption in post-Soviet and Eastern European contexts represents a significant gap in current literature. Most existing studies focus on Western European and North American educational settings, with assumptions about institutional cultures, student-faculty relationships, and technological infrastructure that may not transfer to other contexts. Differences in educational traditions, authority structures, and attitudes toward technology could substantially affect adoption patterns (Selwyn, 2011).

Several researchers have called for empirical studies examining specific factors driving ChatGPT adoption among students. Lund et al. (2023) argue that theoretical frameworks developed for earlier technologies require validation in the ChatGPT context, as the tool's unique characteristics may alter traditional adoption patterns. Similarly, Baskara and Mukarto (2023) emphasize the need for quantitative research identifying statistically significant predictors of adoption to inform evidence-based policy development. This study responds to these calls by empirically examining factors influencing ChatGPT adoption among Georgian university students, testing hypotheses derived from technology acceptance theory and social influence frameworks in a previously unstudied context.

Table 1. Technical data of the study

Research Frame	2500 active students
Collection method	Online (email)
Sampling	Snowball
Response rate	10%
Period	Jan-Feb, 2025
Significance, α	0.05

Research Methodology. This section describes the research design, data collection procedures, measurement instruments, and analytical methods employed to examine factors influencing ChatGPT usage among university students.

Research Design and Sampling

We conducted a cross-sectional quantitative study using primary data collected through a self-administered online questionnaire. The target population comprised active students enrolled at a Georgian university during the 2024-2025 academic year. The research frame included approximately 2,500 currently enrolled students across all academic levels, from first-year undergraduates through master's degree candidates. We employed snowball sampling to recruit participants, distributing the questionnaire link through institutional email channels and encouraging

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respondents to share with fellow students. This non-probability sampling approach was selected due to practical constraints and the exploratory nature of the research in this context. While snowball sampling presents limitations regarding generalizability, it offers advantages for studying technology adoption patterns within interconnected student networks, where peer influence itself constitutes a key variable of interest. Data collection occurred during January and February 2025, a period when ChatGPT had been publicly available for over two years, allowing students sufficient time to become aware of and potentially adopt the technology. The questionnaire remained open for responses throughout this two-month period, with periodic reminders sent to encourage participation.

Of the approximately 2,500 students in the sampling frame, 250 responded to the questionnaire, yielding an initial response rate of 10%. After excluding incomplete responses and data quality checks, the final analytical sample comprised 150 valid responses, representing a 6% effective response rate. While modest, this response rate aligns with typical rates for student email surveys (Nulty, 2008) and provides sufficient statistical power for logistic regression analysis with our number of predictor variables.

Measurement Instruments

The questionnaire incorporated a 10-point Likert scale to measure respondents' attitudes and behaviors regarding ChatGPT usage. This scale provided greater granularity than traditional 5-point or 7-point scales, allowing more nuanced detection of variation in responses while maintaining respondent comprehension (Dawes, 2008). The survey instrument included multiple sections capturing different dimensions of ChatGPT usage and potential influencing factors. Demographic variables measured included age, gender, and academic year. The primary dependent variable assessed whether students use ChatGPT for academic work, coded as a binary outcome (1 = yes, 0 = no).

Independent variables operationalized several theoretical constructs. Perceived usefulness was measured through multiple items assessing whether students find ChatGPT helpful for completing assignments and whether the tool enhances their understanding of complex topics. Perceived ease of use included items measuring how easy students find ChatGPT to use and how quickly they can learn to use it effectively. Social influence factors incorporated measures of peer encouragement and instructor recommendations. Institutional support was assessed through items evaluating university provision of resources and support for ChatGPT usage. Additional items measured whether students use ChatGPT because it makes studying more efficient. The questionnaire underwent pilot testing with a small group of students to identify potential comprehension issues or technical problems before full deployment. Based on pilot feedback, minor wording adjustments were implemented to enhance clarity.

Reliability Analysis

We assessed the internal consistency of the measurement instrument using Cronbach's alpha coefficient. This statistical measure evaluates whether multiple items intended to measure related constructs produce consistent responses, with values ranging from 0 to 1. Generally, alpha values above 0.70 indicate acceptable reliability, while values above 0.80 suggest good reliability (Tavakol & Dennick, 2011). For our 16-item questionnaire, Cronbach's alpha reached 0.868, indicating high internal consistency among the measured items. This suggests that the survey instrument reliably captures the intended constructs and that respondents interpreted questions consistently. All 150 valid cases were included in the reliability analysis, with no missing data requiring listwise deletion.

Analytical Methods

We employed multiple analytical techniques to examine relationships between variables and test research hypotheses. Descriptive statistics provided initial characterization of the sample and identification of usage patterns across demographic groups. Cross-tabulations examined ChatGPT usage rates by academic year, gender, and purpose. The primary analytical method consisted of binary logistic regression, selected as appropriate for examining predictors of a dichotomous dependent variable (whether students use ChatGPT for academic work). Logistic regression estimates the probability that an observation belongs to a particular category based on values of independent variables, making it well-suited for our research questions.

The logistic regression model was specified as follows:

$$\text{logit}(P(Y{=}1)) = \beta_0 + \beta_1{\cdot}\text{Age} + \beta_2{\cdot}\text{Gender} + \beta_3{\cdot}\text{Assignments} + \beta_4{\cdot}\text{Complex\_Topics} + \beta_5{\cdot}\text{Easy\_to\_use} + \beta_6{\cdot}\text{Quickly\_learn} + \beta_7{\cdot}\text{Peers\_Encourage} + \beta_8{\cdot}\text{Instructors\_Recommend} + \beta_9{\cdot}\text{Resources} + \beta_{10}{\cdot}\text{University\_Support} + \varepsilon \quad (1)$$

where logit represents the log-odds function defined as log(p/(1-p)), P(Y=1) indicates the probability of using ChatGPT

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for academic work, subscript i denotes the individual respondent, and ε represents the random error term. The model incorporates demographic controls (age, gender) alongside theoretically relevant predictors derived from technology acceptance frameworks and social influence theory. Each independent variable was measured on the 10-point Likert scale, while gender was coded as a binary variable. We evaluated model fit using multiple indicators. The Cox and Snell R^2 and Nagelkerke R^2 provide pseudo-R^2 measures analogous to explained variance in ordinary least squares regression, though they should be interpreted cautiously due to differences in underlying distributions. The -2 Log Likelihood statistic assesses overall model fit, with smaller values indicating better fit. For each predictor variable, we examined the regression coefficient (B), standard error (S.E.), Wald statistic, and significance level (p-value). The exponential of the coefficient, Exp(B), represents the odds ratio, indicating how the odds of using ChatGPT for academic work change with a one-unit increase in the predictor variable. Statistical significance was evaluated at the $\alpha = 0.05$ level, meaning p-values below 0.05 led to rejection of the null hypothesis of no effect. Complementing the logistic regression, we computed Pearson correlation coefficients to examine linear relationships among key variables related to perceived usefulness and study efficiency. Correlation analysis allows assessment of the strength and direction of bivariate relationships without imposing assumptions about causal direction. Correlations were evaluated for statistical significance using two-tailed tests at the 0.01 significance level.

Research Hypotheses

Based on the literature review and theoretical framework, we formulated five specific hypotheses for empirical testing:

1. **H1:** Students are more likely to use ChatGPT for academic purposes if they receive positive recommendations from peers.
2. **H2:** Students are more likely to use ChatGPT for academic purposes if they receive support from their university.
3. **H3:** Students who find ChatGPT helpful for assignments are more likely to believe it enhances their understanding of complex topics.
4. **H4:** Students who see ChatGPT as improving their understanding tend to use it for study efficiency.
5. **H5:** Students who use ChatGPT for assignments also perceive it as a tool for improving study efficiency.

Hypotheses 1 and 2 were tested through logistic regression analysis, examining whether peer encouragement and university support significantly predict academic ChatGPT usage. Hypotheses 3, 4, and 5 were evaluated through correlation analysis, assessing the strength and significance of relationships among perceived usefulness dimensions.

Limitations

Several methodological limitations warrant acknowledgment. First, the snowball sampling approach and modest response rate limit generalizability to the broader student population. Respondents may differ systematically from non-respondents in technology usage patterns or attitudes. Second, the cross-sectional design prevents causal inference; observed associations may reflect selection effects or reverse causation rather than causal impacts. Third, self-reported data may contain social desirability bias, with students potentially underreporting ChatGPT usage for academic work due to

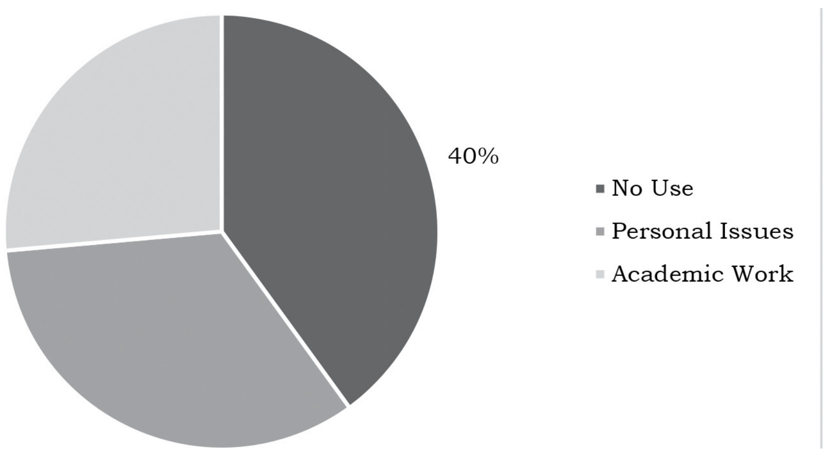

Fig. 1. Purpose of using ChatGPT

Source: built by the author according to the data concerns about integrity. Fourth, the study examines only one institution in one country, limiting transferability to other educational contexts. Finally, the relatively short data collection period provides a snapshot of rapidly evolving technology adoption patterns that may change significantly over time. Despite these limitations, the study offers valuable exploratory insights into the factors influencing ChatGPT adoption among Georgian university students, laying a foundation for future research while providing practical implications for institutional policy development.

Table 2. Technical data of the study

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	154.626[a]	0.289	0.387
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			

Main Results. This section presents findings from the empirical analysis, beginning with descriptive statistics characterizing the sample and usage patterns, followed by results from logistic regression and correlation analyses testing the research hypotheses.

Descriptive Statistics and Usage Patterns

The analytical sample comprised 150 students distributed across various academic levels. Regarding age distribution, the sample demonstrated concentration among traditional university-age students, with the majority falling between 18 and 24 years old. This age distribution aligns with expectations for a predominantly undergraduate population with some graduate students included. Examining ChatGPT usage by purpose reveals important patterns in how students employ the technology. Among the 150 respondents, 40% reported not using ChatGPT at all, while 33.6% use it for personal issues, and 26.4% use it specifically for academic work.

These findings indicate that while ChatGPT has achieved substantial penetration among students, approximately two-fifths remain non-users, and academic applications represent the minority usage category. Personal applications include activities such as casual conversation, entertainment, or non-academic information seeking. Analysis of ChatGPT usage trends by academic year provides additional nuance. For personal issues, first-year students demonstrate the highest usage rate at 40%, declining to 24% for second-year students, 6% for third-year students, 19% for fourth-year students, and 11% for master's students. This pattern suggests that personal usage peaks among newest university students, potentially reflecting novelty effects or greater free time, before declining and then partially rebounding in later years. For academic work, the pattern differs somewhat. First-year students again show the highest rate at 39%, followed by 23% for second-year students, 6% for third-year students, 23% for fourth-year students, and 9% for master's students. The U-shaped pattern for academic usage, with peaks in first and fourth year, may reflect different academic pressures and task types across the curriculum. First-year students may use ChatGPT to adapt to university-level work, while fourth-year students face thesis or capstone project pressures that make AI assistance attractive.

Logistic Regression Analysis

The binary logistic regression model examined predictors of using ChatGPT for academic work. Model fit statistics indicate that the independent variables explain a meaningful portion of variance in the dependent variable. The Cox and Snell R^2 reached 0.289, while the Nagelkerke R^2 achieved 0.387. These pseudo-R^2 values suggest that the independent variables account for approximately 29% to 39% of the variance in ChatGPT usage for academic purposes. While these values appear modest compared to typical R^2 in ordinary least squares regression, they represent acceptable explanatory power for logistic models predicting binary outcomes with human subjects.

The -2 Log Likelihood statistic of 154.626 provides an absolute measure of model fit, though this value is most meaningful when comparing nested models rather than as a standalone indicator. The model estimation terminated successfully after five iterations, indicating convergence and stable parameter estimates with changes less than 0.001 between final iterations. Examining individual predictor variables reveals which factors significantly influence the probability of using ChatGPT for academic work.

Table 3. Technical data of the study

Variables in the Equation							
Step 1a	Age	B -0.083	S.E. 0.098	Wald 0.716	df 1	Sig. 0.397	Exp(B) 0.92
	Gender(1)	-1.881	0.479	15.446	1	0	0.152
	Assignments	0.119	0.126	0.894	1	0.344	1.126
	Complex_Topics	0.077	0.128	0.366	1	0.545	1.08
	Easy_To_Use	-0.013	0.104	0.015	1	0.903	0.987
	Quickly_Learn	0.056	0.136	0.172	1	0.678	1.058
	Peers_Encourage	0.166	0.079	4.387	1	0.036	1.18
	Instructors_Recommend	-0.066	0.097	0.474	1	0.491	0.936
	Resourses	0.048	0.134	0.126	1	0.723	1.049
	University_Support	0.235	0.1	5.492	1	0.019	1.264
	Constant	-2.141	2.212	0.937	1	0.333	0.118

Age demonstrated no statistically significant relationship with academic ChatGPT usage (B = -0.083, Wald = 0.716, p = 0.397). The odds ratio of 0.920 suggests a slight tendency toward lower usage with increasing age, but this relationship did not reach statistical significance at the α = 0.05 level. The lack of age effect may reflect the relatively homogeneous age distribution in the sample or the universal appeal of ChatGPT across the narrow age range represented. Gender emerged as a highly significant predictor of academic ChatGPT usage (B = -1.881, Wald = 15.446, p < 0.001). The odds ratio of 0.152 indicates that female students have approximately 85% lower odds of using ChatGPT for academic work compared to male students, holding other variables constant. This represents a substantial gender difference in adoption patterns, suggesting that male students demonstrate considerably higher likelihood of integrating ChatGPT into their academic work. This finding aligns with some previous research on gender differences in technology adoption, though the magnitude appears larger than typically observed for educational technologies. Variables related to perceived usefulness showed mixed results. The perception that ChatGPT is helpful in completing assignments did not significantly predict actual usage (B = 0.119, Wald = 0.894, p = 0.344, Odds Ratio = 1.126). Similarly, believing that ChatGPT enhances understanding of complex topics failed to achieve statistical significance (B = 0.077, Wald = 0.366, p = 0.545, Odds Ratio = 1.080). These non-significant findings appear counterintuitive given technology acceptance theory's emphasis on perceived usefulness. However, they may reflect that students who already use ChatGPT develop positive perceptions, rather than perceptions driving adoption. Alternatively, the high correlations among usefulness items (discussed below) may create multicollinearity issues that suppress individual effects in the regression model. Perceived ease of use variables also failed to demonstrate significant effects. Neither general ease of use (B = -0.013, Wald = 0.015, p = 0.903, Odds Ratio = 0.987) nor speed of learning (B = 0.056, Wald = 0.172, p = 0.678, Odds Ratio = 1.058) significantly predicted academic usage. These null findings contrast with technology acceptance model predictions that ease of use influences adoption. However, ChatGPT's relatively intuitive interface and widespread publicity may have reduced variation in perceived ease of use, making it a less discriminating predictor than for more complex technologies.

Instructor recommendations showed no significant relationship with student usage (B = -0.066, Wald = 0.474, p = 0.491, Odds Ratio = 0.936). The slightly negative coefficient, though non-significant, suggests that instructor recommendations may have neutral or even slightly suppressive effects on usage. This could reflect that instructors primarily raise ChatGPT in contexts of warning about academic integrity rather than endorsement, or that students value peer recommendations more highly than faculty guidance for technology adoption decisions. University provision of resources for ChatGPT usage did not achieve statistical significance (B = 0.048, Wald = 0.126, p = 0.723, Odds Ratio = 1.049). This null finding appears surprising given theoretical expectations

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about resource availability facilitating adoption. However, it may indicate that students primarily access ChatGPT through personal devices and accounts rather than university-provided infrastructure, making institutional resources less relevant to adoption decisions. Two variables demonstrated statistically significant positive effects on academic ChatGPT usage. Peer encouragement significantly predicted adoption (B = 0.166, Wald = 4.387, p = 0.036, Odds Ratio = 1.180). The odds ratio indicates that each one-unit increase on the 10-point Likert scale measuring peer encouragement associates with an 18% increase in the odds of using ChatGPT for academic work. This finding strongly supports Hypothesis 1, confirming that students receiving positive recommendations from peers demonstrate higher probability of ChatGPT adoption. The result aligns with extensive research on peer influence in technology adoption and suggests that student-to-student communication plays a crucial role in diffusing ChatGPT usage through academic communities. University support emerged as the strongest predictor in the model (B = 0.235, Wald = 5.492, p = 0.019, Odds Ratio = 1.264). Each one-unit increase in perceived university support associates with a 26.4% increase in the odds of using ChatGPT for academic work. This finding provides strong support for Hypothesis 2, indicating that institutional endorsement and support significantly facilitate student adoption. The distinction between this significant effect and the non-significant effect of university resources suggests that general institutional support, potentially including policy clarity and cultural acceptance, matters more than specific resource provision. The constant term did not achieve statistical significance (B = -2.141, Wald = 0.937, p = 0.333), which is common in logistic regression and does not affect interpretation of predictor variables. These results indicate that social and institutional factors, specifically peer encouragement and university support, represent the primary drivers of ChatGPT adoption for academic purposes among Georgian university students. Individual perceptions of usefulness and ease of use, while theoretically important, did not demonstrate independent effects in this model, possibly due to multicollinearity or because they operate indirectly through social influence processes.

Correlation Analysis

Pearson correlation analysis examined relationships among three key variables related to perceived usefulness and efficiency. All three pairwise correlations achieved high magnitudes and statistical significance at the $p < 0.01$ level, providing strong support for Hypotheses 3, 4, and 5. The correlation between finding ChatGPT helpful in completing assignments and believing it enhances understanding of complex topics reached 0.784 ($p < 0.001$). This strong positive correlation supports Hypothesis 3, indicating that students who perceive ChatGPT as useful for one academic purpose (assignment completion) tend strongly to perceive it as useful for another purpose (conceptual understanding). The relationship suggests that perceived usefulness generalizes across different learning activities rather than remaining narrowly task-specific. The correlation between believing ChatGPT enhances understanding of complex topics and using it because it makes studying more efficient achieved 0.686 ($p < 0.001$). This moderately strong positive correlation

Table 4. Correlation Table

Correlations				
		ChatGPT is helpful in completing my assignments	ChatGPT enhances my understanding of complex topics	I use ChatGPT because it makes studying more efficient
ChatGPT is helpful in completing my assignments	Pearson Correlation	1	0.784**	0.664**
	Sig. (2-tailed)		0	0
	N	150	150	150
ChatGPT enhances my understanding of complex topics	Pearson Correlation	0.784**	1	0.686**
	Sig. (2-tailed)	0		0
	N	150	150	150
I use ChatGPT because it makes studying more efficient	Pearson Correlation	0.664**	0.686**	1
	Sig. (2-tailed)	0	0	
	N	150	150	150
**. Correlation is significant at the 0.01 level (2-tailed).				

supports Hypothesis 4, demonstrating that students who perceive learning benefits also tend to value efficiency gains. The relationship indicates that students view ChatGPT as simultaneously deepening understanding and saving time, rather than seeing these as competing benefits.

Finally, the correlation between finding ChatGPT helpful in completing assignments and using it for study efficiency reached 0.664 ($p < 0.001$). This moderately strong positive correlation supports Hypothesis 5, showing that students who value ChatGPT for specific tasks also perceive general productivity benefits. Again, the finding suggests complementary rather than competing dimensions of perceived usefulness. The high correlations among all three variables indicate substantial overlap in how students perceive ChatGPT's benefits. Students who find it helpful in any one dimension tend to find it helpful across multiple dimensions. This clustering of perceptions may explain why individual usefulness variables failed to show independent effects in the logistic regression; the high intercorrelations create multicollinearity that makes it difficult to isolate unique contributions of each variable when included simultaneously in a model.

Summary of Hypothesis Testing

All five research hypotheses received empirical support. Hypothesis 1, predicting that peer encouragement increases likelihood of ChatGPT usage for academic purposes, was supported through statistically significant positive effects in logistic regression. Hypothesis 2, predicting that university support increases usage likelihood, similarly received strong support as the most powerful predictor in the regression model. Hypotheses 3, 4, and 5, predicting positive correlations among different dimensions of perceived usefulness and efficiency, all achieved strong empirical support through highly significant correlation coefficients. These findings collectively indicate that social and institutional factors play primary roles in driving ChatGPT adoption for academic work, while different dimensions of perceived usefulness demonstrate strong intercorrelations, forming a relatively unified construct in students' minds.

Conclusion. This study examined factors influencing ChatGPT usage among university students in Georgia, contributing to the emerging literature on artificial intelligence adoption in educational settings. Using quantitative data from 150 students and employing logistic regression and correlation analyses, we identified peer encouragement and university support as the most significant predictors of ChatGPT adoption for academic purposes. Additionally, we established strong positive correlations among different dimensions of perceived usefulness, including assignment assistance, conceptual understanding, and study efficiency. The findings carry important theoretical and practical implications while also pointing toward directions for future research.

The central theoretical contribution lies in validating and extending technology acceptance frameworks to the context of generative AI tools in education. While the Technology Acceptance Model traditionally emphasizes perceived usefulness and ease of use as primary drivers of adoption, our findings suggest that in the ChatGPT context, social and institutional factors may play even more decisive roles. Peer encouragement emerged as a statistically significant predictor, confirming the relevance of social influence theory and research on peer effects in educational technology adoption. The finding that university support represents the strongest predictor underscores the importance of organizational context and institutional legitimation for emerging technologies, particularly those carrying potential ethical concerns or policy ambiguity.

The strong gender difference observed in ChatGPT adoption, with male students demonstrating substantially higher usage rates for academic work, raises important questions about equity in AI tool access and benefits. While gender differences in technology adoption have been documented across various contexts, the magnitude observed here appears particularly large. This finding suggests that interventions promoting equitable AI tool usage should pay careful attention to gender dynamics, potentially through targeted outreach, female-friendly educational materials, or addressing underlying factors that may discourage female students from experimenting with AI technologies.

The high correlations among perceived usefulness dimensions indicate that students view ChatGPT benefits holistically rather than compartmentally. Students who find the tool helpful for assignments also tend to believe it enhances understanding and improves efficiency. This pattern suggests that ChatGPT provides bundled benefits that together create positive user experiences, rather than excelling in isolated use cases. For educational practice, this implies that universities should consider comprehensive approaches to AI integration that leverage multiple benefit dimensions simultaneously rather than positioning these tools narrowly for specific tasks.

The practical implications for universities are substantial. First, the critical importance of university support as a predictor of adoption suggests that institutional policy clarity significantly affects student behavior. Universities that clearly communicate appropriate usage boundaries, provide guidance on effective ChatGPT integration, and signal institutional acceptance of responsible AI use will likely see more widespread and potentially more ethical adoption than institutions maintaining ambiguous or purely restrictive stances. Second, the significance of peer influence suggests that student-to-student learning and peer ambassador programs could effectively promote responsible ChatGPT usage. Universities might consider training student leaders in effective AI tool usage and empowering them to share knowledge with fellow students. Third, institutions should develop workshops and resources educating students about both opportunities and limitations of ChatGPT, addressing concerns about plagiarism and data privacy while demonstrating productive use cases.

For researchers, these findings establish a baseline understanding of ChatGPT adoption patterns in the Georgian context while raising numerous questions for future investigation. Longitudinal research tracking how adoption patterns evolve as the technology matures and as universities formalize policies would provide valuable insights into technology diffusion processes. Qualitative research exploring the mechanisms through which peer influence operates, examining what specific messages or demonstrations prove most persuasive, could complement these quantitative findings. Comparative studies examining adoption patterns across different national and institutional contexts would test the generalizability of these results and identify culturally or structurally contingent factors. Research examining academic outcomes associated with different usage patterns would address crucial questions about whether ChatGPT ultimately enhances or undermines learning.

The study's limitations suggest important caveats for interpreting results. The cross-sectional design prevents causal claims; observed associations may reflect reverse causation or selection effects rather than causal impacts of predictors on adoption. The modest sample size from a single institution limits generalizability to broader populations. The reliance on self-reported data introduces potential social desirability bias, possibly leading to under-reporting of academic ChatGPT usage given integrity concerns. For government and policymakers, the findings suggest that top-down regulations alone may prove insufficient for governing AI use in education. The dominance of peer and institutional influences implies that effective governance requires working through educational institutions and student networks rather than relying primarily on external mandates. Policymakers should consider supporting universities in developing context-appropriate AI usage policies, providing resources for faculty and student training, and facilitating knowledge sharing about effective practices across institutions. Looking forward, universities face critical choices about how to respond to ChatGPT and similar generative AI tools. Restrictive approaches that attempt to prohibit or heavily police usage may prove both practically difficult to enforce and educationally counterproductive, potentially driving usage underground and preventing development of responsible usage norms. Alternatively, laissez-faire approaches that ignore these technologies risk allowing problematic usage patterns to become entrenched and failing to help students develop critical AI literacy. The findings suggest that a middle path emphasizing clear institutional guidance, peer learning, and deliberate integration of AI tools into curricula while maintaining academic integrity standards may prove most effective. The emergence of ChatGPT represents a transformative moment for higher education, comparable perhaps to the introduction of internet search engines or Wikipedia in terms of potential impact on student research and learning practices. Unlike these earlier technologies, however, ChatGPT's ability to generate original-seeming text raises more acute questions about authorship, intellectual development, and assessment validity. The challenge for educational institutions is to harness the genuine learning benefits these tools offer, including personalized explanation, rapid feedback, and assistance with routine tasks, while preserving core educational values around critical thinking, intellectual honesty, and authentic skill development.

This study's findings that peer networks and institutional support drive adoption suggest that universities possess more

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influence over how these technologies integrate into educational practice than they might assume. By thoughtfully shaping institutional policies, creating supportive infrastructures, and facilitating peer learning communities, universities can guide ChatGPT adoption toward patterns that enhance rather than undermine educational quality. The key lies in moving beyond binary acceptance or rejection toward nuanced integration that acknowledges both opportunities and risks while empowering students to make informed, ethical choices about AI tool usage.

In conclusion, ChatGPT adoption among Georgian university students is primarily driven by social and institutional factors rather than individual perceptions of usefulness or ease of use alone. Peer encouragement and university support emerge as the strongest predictors of academic usage, suggesting that technology diffusion in educational settings operates heavily through social influence mechanisms. Universities seeking to promote responsible AI integration should focus on providing clear guidance and support while leveraging peer networks to disseminate effective practices. As generative AI technologies continue evolving and proliferating, understanding the factors that shape student adoption patterns will remain essential for developing policies and practices that maximize educational benefits while mitigating potential harms.

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ФАКТОРИ, ЩО ВПЛИВАЮТЬ НА ВИКОРИСТАННЯ CHATGPT СТУДЕНТАМИ ВИЩИХ НАВЧАЛЬНИХ ЗАКЛАДІВ: ЕМПІРИЧНЕ ДОСЛІДЖЕННЯ У ГРУЗІЇ

У цьому дослідженні вивчаються ключові чинники, що впливають на поширення ChatGPT серед студентів університетів Грузії, що поповнює зростаючу кількість наукових праць, присвячених інтеграції штучного інтелекту у вищу освіту. Оскільки генеративні інструменти штучного інтелекту стають дедалі поширенішими в академічних середовищах у всьому світі, розуміння факторів, що сприяють або гальмують їхнє впровадження в конкретних соціокультурних та інституційних контекстах, має вирішальне значення. Це дослідження заповнює помітну прогалину в існуючій науковій літературі, оскільки пострадянські освітні середовища залишаються значно недопредставленими в дослідженнях щодо впровадження технологій, незважаючи на їхні особливі структурні та культурні характеристики.

Дослідження базується на первинних даних, зібраних серед 150 студентів одного з грузинських університетів за допомогою онлайн-опитування з використанням 10-бальної шкали Лайкерта. Для виявлення статистично значущих предикторів використання ChatGPT в академічних цілях було застосовано логістичний регресійний аналіз. Аналітична модель поєднує теорію соціального впливу з усталеними моделями прийняття технологій, пропонуючи теоретично обґрунтовану перспективу для інтерпретації поведінки щодо впровадження в контексті інструментів генеративного штучного інтелекту.

Результати дослідження показують, що заохочення з боку однолітків та інституційна підтримка є найбільш впливовими факторами, що сприяють впровадженню ChatGPT, з коефіцієнтами шансів 1,180 та 1,264 відповідно. Ці результати підкреслюють ключову роль, яку відіграють соціальні мережі та політика університетів у формуванні готовності студентів використовувати інструменти штучного інтелекту у своїх навчальних процесах. Також було виявлено сильну позитивну кореляцію між сприйняттям корисності інструменту для виконання завдань, покращенням розуміння складних тем та загальною ефективністю навчання, що свідчить про те, що при оцінці інструментів штучного інтелекту студентів насамперед мотивують відчутні академічні переваги.

Було досліджено гендерні відмінності у моделях впровадження: чоловіки-студенти продемонстрували статистично значущу вищу ймовірність використання ChatGPT для академічної роботи порівняно зі своїми колегами-жінками. Цей висновок підкреслює важливість врахування демографічних змінних при розробці програм з грамотності у сфері штучного інтелекту та структур інституційної підтримки.

У дослідженні також аналізується суперечність між сприянням технологічним інноваціям та дотриманням академічної доброчесності у вищих навчальних закладах. У той час як університети намагаються подолати виклики, пов'язані з генеративною штучною інтелігенцією, отримані результати містять практичні рекомендації щодо розробки науково обґрунтованих стратегій інтеграції ШІ. У підсумку це дослідження закликає до збалансованого інституційного підходу, який сприятиме розвитку цифрової компетентності та рівному доступу, водночас захищаючи принципи оригінальної наукової роботи.

Ключові слова: ChatGPT, штучний інтелект в освіті, прийняття технологій, вплив однолітків, підтримка університету.

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