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Personality Traits And Antecedents Of AI Chatgpt Adoption – Evidence From University Students

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Abstract

Purpose: The purpose of this study is to investigate the impact of personality traits and external factors on the use of ChatGPT, a generative AI tool, among university students. Understanding the psychological and technological factors of AI use is critical for optimizing learning outcomes and increasing digital engagement as it becomes more integrated in higher education.

Design/Methodology/Approach: The research takes a quantitative approach, with a standardized questionnaire delivered to university students. The study is based on the Big Five Personality Traits framework and known technology adoption frameworks, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The data will be evaluated using statistical methods such as SPSS to investigate the correlations between personality traits, perceived utility, simplicity of use, and behavioural intent to use ChatGPT.

Findings: According to preliminary expectations, personality traits such as openness and conscientiousness are predicted to correlate positively with the perceived usefulness and simplicity of use of ChatGPT. Additionally, social influence and favorable environments are predicted to have a substantial impact on adoption behavior. These findings are intended to emphasize the complex interaction of individual psychological elements and external technical cues in affecting user behaviour.

Practical Implications: The findings of this study can help educators, developers, and institutions create AI-based instructional tools that are suited to different personality types and user preferences. Institutions may boost student engagement, increase learning efficiency, and promote responsible AI use in academic contexts by matching implementation techniques with student behavior and personality profiles.

Originality/Values: This study offers new insights by combining personality psychology with technology adoption frameworks to evaluate ChatGPT usage in higher education. It addresses a significant research vacuum by concentrating on both system-related aspects and user-centric psychological motivations, providing a more comprehensive understanding of AI adoption behaviour.

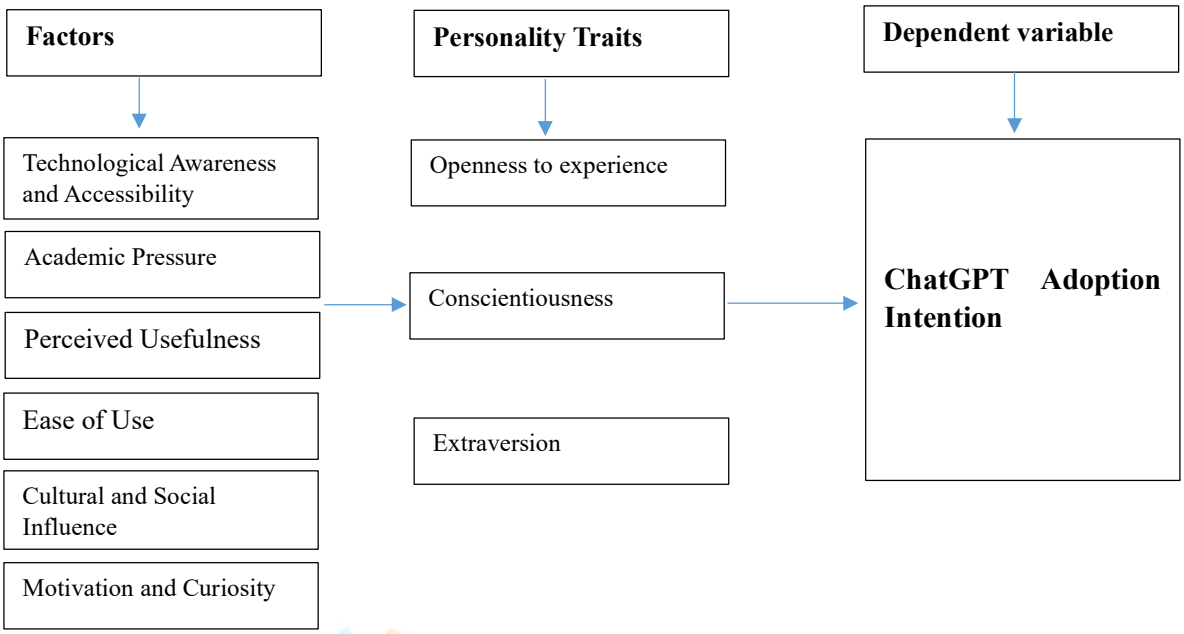
Keywords: Personality Traits, ChatGPT Adoption, University Students, Technology Acceptance Model (TAM), UTAUT, AI in Education, Big Five Model, AI Tools, Higher Education, and Digital Learning

Introduction

The use of artificial intelligence (AI) tools in higher education, such as ChatGPT, is fast changing the landscape of teaching, learning, and student involvement. Despite its ubiquitous availability, the adoption of ChatGPT among university students varies significantly, affected by both external and internal factors. While some students eagerly use these tools for writing, ideation, and research support, others are hesitant due to worries about accuracy, abuse, or ethical consequences. Prior research has extensively investigated the technology acceptance of AI tools using models such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which emphasize the importance of perceived usefulness, ease of use, and social influence in shaping user behavior. Recent research has expanded on these models by include psychological aspects such as trust, privacy concerns, and perceived danger (Zarouali et al., 2021; Dwivedi et al., 2023). However, there is still a theoretical vacuum in understanding how personality factors influence the adoption of AI-driven chatbots such as ChatGPT. Personality, as defined by the Big Five Personality Traits model (Costa & McCrae, 1992), has been linked to individual preferences and technological engagement patterns. Individuals with high openness to experience, for example, are more willing to experiment with new technologies, whereas those with high neuroticism may be resistant due to worry or distrust (McElroy et al., 2007; Devaraj et al., 2008). Recent empirical evidence from Rauschnabel et al. (2022) and Vrontis et al. (2021) indicates that personality considerably moderates AI adoption behaviour, particularly in scenarios involving perceived intelligence and system autonomy. Moreover, students' capacity to use ChatGPT must be considered in the context of their learning environment and social influences. Zhang et al. (2023) and Nguyen et al. (2023) found that academic culture, peer behavior, and institutional policies all had an impact on students' adoption of generative AI tools, in addition to usability and trust. Despite these developments, academic literature contains little research on the interaction of personality traits with other influencing factors, such as technical, psychological, and social variables. There is a need to analyze how students' intrinsic psychological profiles interact with environmental enablers or barriers to form their behavioral intentions towards the adoption of AI tools in education. As a result, the purpose of this study is to fill a gap by looking into the impact of personality traits, as well as technology-related factors (e.g., perceived ease of use, perceived usefulness), psychological constructs (e.g., trust, attitude), and social factors (e.g., peer influence), on ChatGPT adoption by university students. By doing so, the study adds to the increasing body of knowledge in AI adoption research and has important implications for educational institutions seeking to promote ethical, effective, and inclusive AI integration in student learning.

Theoretical Framework

This study's is based on the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which have long been used to explain people's intentions to adopt and use technological innovations. TAM focuses on two major predictors of technology adoption: perceived usefulness (PU) and perceived ease of use (PEOU), whereas UTAUT extends on these by considering social impact, facilitating factors, and behavioral intention. However, the dynamic and personalized character of AI tools such as ChatGPT necessitates the incorporation of individual psychological elements. This study uses the Big Five Personality Traits model (Costa & McCrae, 1992) as an upstream variable to explain user variability in ChatGPT adoption. Openness to experience, conscientiousness, and neuroticism have been shown to influence technology usage habits, with openness frequently associated with curiosity and innovation adoption, and neuroticism with anxiety and technological aversion (Devaraj et al., 2008). Furthermore, attitudes toward AI, trust in the system, and perceived risk are viewed as psychological variables influencing adoption behavior, building on recent research on AI ethics and trust (Zarouali et al., 2021; Vrontis et al.,2021). Social factors such as social influence and academic norms are thought to play an important role in determining students' behavioral intentions. This theoretical framework, which combines TAM and UTAUT components with personality traits and social-psychological variables, provides a comprehensive lens through which to examine the complicated decision-making process that drives ChatGPT adoption among university students.



Literature Review

The use of AI technologies such as ChatGPT in higher education is influenced by a complex interplay of psychological, technological, and contextual variables. Psychological hurdles, such as doubts about AI's correctness, fears of academic dishonesty, and concerns about dependency, frequently impede student involvement. These issues are exacerbated by technology constraints such as low digital literacy, limited device access, and unfamiliarity with AI systems. Zarouali et al. (2021) found that anxiety and lack of confidence have a substantial impact on preparedness to adopt AI. Despite these challenges, AI use in academic contexts is increasing, with students using applications such as ChatGPT for idea development, proofreading, concept clarification, and time management. This trend demonstrates an increasing dependence on intelligent technologies to improve learning results, while engagement varies according to student confidence and tech savvy. Nguyen et al. (2023) highlight the global trend toward hybrid learning, which combines traditional teaching with AI. Theoretical approaches like the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Big Five Personality Traits serve as a solid foundation for studying adoption behaviours. TAM focuses on perceived usefulness and ease of use, whereas UTAUT considers social impact and enabling factors. The Big Five paradigm goes deeper by addressing personality variations, associating traits like openness and conscientiousness to higher adoption rates and neuroticism to resistance (McElroy et al., 2007; Devaraj et al., 2008). Institutional considerations also influence adoption, with colleges that promote digital preparedness, provide training, and encourage AI research seeing higher student engagement (Zhang et al., 2023). Student autonomy, institutional support, and personal motivation all play important roles in determining engagement. According to Deci and Ryan's Self-Determination Theory (1985), curiosity and personal growth motivate students to investigate AI technologies such as ChatGPT beyond their initial use, incorporating them into meaningful learning opportunities. However, ethical questions about data privacy, disinformation, and academic integrity remain prevalent. Trust is an important moderator—when students believe AI systems are trustworthy and adhere to ethical standards, they are more likely to utilize them responsibly (Gefen and Straub, 2000). Adoption varies between disciplines and institutions; students in technical sectors like engineering frequently exhibit increased usage due to familiarity with AI, whereas students in the humanities may be more wary due to grading subjectivity and ethical scrutiny. Institutions with strong digital strategy and an openness to AI experimentation enable broader and

more imaginative use. Finally, digital competency, gender, and social issues influence AI adoption. Students with high digital literacy are more likely to use tools like ChatGPT efficiently. Research suggests gender inequalities, with male students emphasizing utility and females emphasizing trust and user experience (Teo, 2011). Furthermore, sociocultural circumstances, such as collectivist versus individualist beliefs, determine how peer behaviours and group norms impact AI adoption decisions. Together, these dimensions provide a thorough knowledge of the various elements that influence student engagement with AI in higher education.

Research Gap

Despite giving helpful insights, the study has some significant limitations that suggest crucial areas for future research. First, the findings' generalizability is limited because the sample was selected entirely from a single institution. Variations in digital infrastructure, teacher participation, AI integration plans, and student demographics between universities and countries may have a substantial impact on ChatGPT adoption rates. Furthermore, the impact of cultural dimensions such as collectivism vs individualism, power distance, and localized academic norms has received little attention, despite the fact that these characteristics have been proven to influence technological acceptance in a variety of educational settings. A cross-institutional and cross-cultural strategy is thus required to improve the external validity of the findings. Second, while the literature review mentions trust and ethical issues, these variables are not included in the empirical model. Trust in AI systems, worries about academic integrity, data privacy, and the perceived risk of disinformation all have a significant impact on students' opinions toward tools like ChatGPT. Their exclusion highlights a serious gap, especially given the increased emphasis on responsible and ethical AI use in education. Third, the study's findings call into question conventional technology adoption models such as TAM and UTAUT, as characteristics such as perceived ease of use and social influence, which are generally strong predictors, were found to be weak or even negatively connected with ChatGPT use. This disparity shows that standard models may not adequately capture the nuanced, customized, and ethical aspects of AI adoption in educational settings, emphasizing the need for revised or AI-specific theoretical frameworks. Finally, the cross-sectional aspect of the study limits our understanding of how adoption practices change over time. Because students' trust, usage patterns, and ethical considerations can change as they get increasingly exposed to AI tools, a longitudinal design would provide a more comprehensive, dynamic view of adoption trends. This would be especially important for developing adaptable, forward-thinking strategies for AI inclusion in education.

Hypothesis

Hypothesis : A hypothesis is a proposed explanation for a specific reason. To be considered a reliable theory, it must be testable. Experts often base their hypotheses on prior perceptions that cannot be fully explained by current reasonable theories. Although the terms "hypothesis" and "hypotheses" are commonly used interchangeably, a sound theory differs from a well-founded supposition.A working supposition is a hypothesis presented for further inquiry based on an ill-defined metric or concept.

Null Hypothesis is taken as H0, and the alternate hypothesis is taken as H1

Hypotheses for Factors Influencing AI-ChatGPT Adoption

H01: Technological awareness and accessibility have no significant impacts on AI-ChatGPT adoption

H11: Technological awareness and accessibility significantly impact AI-ChatGPT adoption.

H02: Academic pressure has no significant impact on AI-ChatGPT adoption H12: Academic pressure significantly impacts AI-ChatGPT adoption.

H03: Perceived usefulness has no significant impact on AI-ChatGPT adoption.

H13: Perceived usefulness significantly impacts AI-ChatGPT adoption.

H04: Ease of use has no significant impact on AI-ChatGPT adoption

H14: Ease of use significantly impacts AI-ChatGPT adoption.

H05: Cultural and social influences have no significant impacts on AI-ChatGPT adoption.

H15: Cultural and social influences significantly impact AI-ChatGPT adoption.

Hypotheses for the Impact of Personality Traits on AI-ChatGPT Adoption

H06: Openness to experience does not significantly impact AI-ChatGPT adoption.

H16: Openness to experience significantly impacts AI-ChatGPT adoption.

H07: Conscientiousness does not have a significant impact on AI-ChatGPT adoption.

H17: Conscientiousness significantly impacts AI-ChatGPT adoption.

H08: Extraversion does not significantly impact AI-ChatGPT adoption.

H18: Extraversion significantly affects AI-ChatGPT adoption.

H09: Motivation and curiosity have no significant effect on AI-ChatGPT adoption

H19: Motivation and curiosity significantly impact AI-ChatGPT adoption.

H01 & H11: Technological awareness and accessibility

Technology awareness and accessibility are critical factors in influencing how students use AI technologies such as ChatGPT. Individuals with better awareness and easier access to technology are more likely to adopt it, according to Venkatesh et al. (2003), citing the Unified Theory of Acceptance and Use of Technology (UTAUT). Students who are well-informed about ChatGPT and have easy access to it via gadgets or steady internet are more likely to use it for academic activities.

H02 & H12: Academic pressure

Academic pressure may motivate students to seek help from AI tools. Tarhini et al. (2015) underlined that external demands, such as workload and deadlines, frequently lead users to adopt technology that requires less effort. Students who are under a lot of academic stress may use ChatGPT to find quick solutions or generate content to help them cope with their studies.

H03 & H13: Perceived usefulness

ChatGPT's perceived utility, or how beneficial students find it, has a significant impact on its uptake. According to Davis's (1989) Technology Acceptance Model (TAM), people are more inclined to adopt technology that allows them to execute tasks more effectively. If students find ChatGPT useful for comprehending concepts, completing assignments, or studying for tests, they will be more likely to use it.

H04 & H14: Ease of use

Ease of use is a significant determinant of technology adoption. According to Davis (1989), if students find ChatGPT easy to use with no technological complications, they are more likely to use it. A simple interface and quick responses improve the experience, encouraging non-technical users to adopt it

H05 & H15: Cultural and social influences

Social norms and cultural setting might influence user behaviour about AI adoption. Bhattacherjee (2001) and Venkatesh et al. (2003) demonstrated how peer behaviour and society approval influence individual decisions. If ChatGPT is perceived as common or valuable among a student's classmates or within their culture, they are more likely to adopt it.

H06 & H16: Openness to experience

Personality factors such as openness curiosity, inventiveness, and a willingness to try new things are substantially associated with AI tool adoption. According to McCrae and Costa's (1999) Big Five Personality Theory, students who are open to new experiences are more likely to experiment with novel technologies such as ChatGPT, resulting in increased adoption.

H07 & H17: Conscientiousness

Conscientious students are organized and goal-oriented, and they may use AI tools to increase their academic efficiency. John and Srivastava (1999) discovered that conscientious people Favor tools that help them retain discipline and achieve deadlines, implying that ChatGPT could help them learn more efficiently.

H08 & H18: Extraversion

Extraverted students, who are typically more gregarious and outspoken, may use AI technologies such as ChatGPT to engage in interactive learning. Costa and McCrae (1992) proposed that extraverts enjoy stimulating situations, and ChatGPT's conversational nature may appeal to their learning preferences.

H09 & H19: Motivation and curiosity

Internal factors such as motivation and curiosity motivate people to experiment with and use new technology. According to Deci and Ryan's (1985) Self-Determination Theory, intrinsic motivation and a curious mentality encourage more experimental actions, such as experimenting with new tools like ChatGPT for academic enrichment or personal learning.

Methodology

The research design utilized a quantitative approach to analyse factors which drive university students to adopt AI-ChatGPT. Researchers constructed and distributed a structured online survey through Google Forms to obtain efficient data. The questionnaire contained three main sections which included
(1) students' interactions with and opinions about ChatGPT,
(2) the evaluation of Five Big Traits and
(3) social demographic profiles.
The initial segment of the survey evaluated fundamental adoption criteria that included the assessment of usefulness alongside ease of use coupled with academic stress and motivational variables and technological resource accessibility. Personality traits were evaluated in the second section through the BFI-S scale (Schupp & Gerlitz, 2008) along with validated items from Lang et al. (2001). Random ordering of items throughout the personality traits section functioned as an approach to decrease response bias.
The third survey section gathered respondent information about their age along with gender and both academic enrolment level and school affiliation. Every survey response could be measured through a five-point Likert scale which ran from 1 (Strongly Disagree) up to 5 (Strongly Agree). SPSS and Microsoft Excel tools analysed the gathered data with descriptive statistics and regression analysis together with ANOVA and correlation analysis.

Sample

The research received 200 validated responses from university students studying at undergraduate and postgraduate and doctoral levels. A simple random sampling technique identified participants who maintained an equal representation among different academic level groups and academic research areas. The online survey was distributed during January to March 2025.

A wide range of demographics characterized the study participants because they spread evenly between males and females while most subjects came from ages 20 to 30. The research participants showed familiarity with ChatGPT by either using it frequently or attempting its use for academic purposes. The studied population consisted of participants drawn from multiple educational establishments including public and private institutions distributed across various geographical zones.

The wider participant sample base enabled researchers to comprehend universal student behaviour when interacting with Artificial Intelligence tools particularly ChatGPT and its adoption patterns and determining impact factors.

Data Analysis and Interpretation

This research study examined how personality traits and environment factors influence university students' acceptance of ChatGPT using a systematic evaluation methodology. The researchers measured how psychological elements together with situation-dependent variables affect AI tool usage through regression analysis and ANOVA testing and correlation analysis. The researchers obtained data from 200 students via structured questionnaires before cleaning and processing them using SPSS together with Microsoft Excel for effective interpretation.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.772[a]	.596	.577	.51186	.596	31.277	9	191	.000	1.881

a. Predictors: (Constant), MC Average , OE Averages, CSI Averages, EU Averages, AP Averages, PU Average, CT Averages, EV Averages, TAA Averages

b. Dependent Variable: DV Averages

Fig 1

The predictive model achieved high accuracy because it registered a 0.772 correlation coefficient and a 0.596 R square value which implies the chosen variables explain 59.6% of the changes in ChatGPT adoption. The F-statistic value of 31.277 with a significance level ($p < 0.001$) proved the statistical significance of the entire regression model.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	73.753	9	8.195	31.277	.000[b]
	Residual	50.042	191	.262		
	Total	123.795	200			

a. Dependent Variable: DV Averages

b. Predictors: (Constant), MC Average , OE Averages, CSI Averages, EU Averages, AP Averages, PU Average, CT Averages, EV Averages, TAA Averages

Fig 2

Analysis of variance measurements showed the regression sum of squares (73.753) exceeded the residual sum of squares (50.042) thus demonstrating the independent variables play a major role in dependent variable variation. The model strength became apparent through the high mean square for regression (8.195) being greater than the residual value (0.262).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.149	.148		1.012	.313					
	TAA Averages	.163	.114	.139	1.428	.155	.648	.103	.066	.222	4.502
	AP Averages	.163	.095	.146	1.716	.088	.654	.123	.079	.294	3.401
	PU Average	.052	.090	.049	.582	.561	.588	.042	.027	.297	3.364
	EU Averages	-.117	.089	-.103	-1.311	.191	.545	-.094	-.060	.342	2.924
	CSI Averages	-.131	.092	-.111	-1.421	.157	.539	-.102	-.065	.346	2.893
	OE Averages	.493	.094	.431	5.253	.000	.726	.355	.242	.314	3.188
	CT Averages	.300	.105	.251	2.858	.005	.667	.203	.131	.274	3.644
	EV Averages	.092	.104	.082	.878	.381	.648	.063	.040	.242	4.131
	MC Average	-.084	.106	-.067	-.793	.429	.542	-.057	-.036	.296	3.378

a. Dependent Variable: DV Averages

Fig 3

Research findings show that Openness to Experience ($\beta = 0.431$, $p < 0.001$) together with Conscientiousness ($\beta = 0.251$, $p = 0.005$) have positively influenced student adoption of ChatGPT. The acceptance rate of AI tools for academic purposes by students mainly depends on their openness to new experiences combined with their degree of organization and self-discipline. Academic Pressure ($\beta = 0.146$) together with Technological Awareness ($\beta = 0.139$) generated moderate yet insignificant relationships with adoption behaviour. The negative relationship between Ease of Use and Cultural/Social Influence with adoption behaviour contradicts core concepts within TAM and UTAUT traditional models.

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.9400	4.7047	2.2699	.60726	201
Residual	-1.38127	1.55123	.00000	.50021	201
Std. Predicted Value	-2.190	4.010	.000	1.000	201
Std. Residual	-2.699	3.031	.000	.977	201

a. Dependent Variable: DV Averages

Fig 4

The predictive model showed unbiased distribution according to residual analysis because residuals demonstrated a mean value of 0.00000 and standard deviation at 0.977. The normal distribution pattern of residuals became evident through both the histogram output and Normal P-P plot results that showed most data points concentrated near the mean and followed closely with the diagonal reference line. The few present outliers did not substantially change the general analysis results.

The research evidence shows that psychological characteristics such as conscientiousness and openness prove stronger than technological and social elements when predicting Chat GPT adoption. The research results show why human personality should become a critical element when implementing AI technology in educational settings.

Major Findings

This research has identified a positive link between the adoption of AI-Chat GPT by university students and two personality traits: Openness to Experience and Conscientiousness. The traits studied significantly affect student behaviour when they decide to use AI tools for academic work. The model generated an R-square value of 0.596 which means the examined elements explain sixty percent of variables affecting Chat GPT usage. The model shows good predictive strength, but additional unanalysed variables may lead to improved clarification of its predictive abilities. The F-statistic measures 31.277 together with a p-value of 0.000 shows that the regression model has significant meaning. Thus, the research hypothesis proves valid which states that psychological elements and contextual components play a meaningful role in AI-Chat GPT adoption.

The research data demonstrated that Openness to Experience was the strongest contributing factor ($\beta = 0.431$, $t = 5.253$, $p < 0.001$) that makes students with curious and imaginative personalities more likely to adopt ChatGPT. The data demonstrates that high-level self-discipline and organizational abilities (conscientiousness) directly influence students' behaviour to adopt AI tools in their academic work ($\beta = 0.251$, $t = 2.858$, $p = 0.005$). Academic Pressure ($\beta = 0.146$, $p = 0.088$) together with Technological Awareness ($\beta = 0.139$, $p = 0.155$) demonstrated weak positive relationships with ChatGPT usage but their statistical effects remained insignificant. External pressures and technological awareness maintain only a limited impact on AI usage even though they do play a partial role.

The associations between Ease of Use and Cultural/Social Influence variables were either negligible or negative thus indicating traditional technology acceptance models factors such as TAM and UTAUT might not impact this situation significantly. The Analysis of Variances (ANOVA) showed moderate correlations between independent variables up to 4.502 and down to 2.893 VIF levels although both figures remained inside valid statistical boundaries which strengthened the validity of this regression analysis.

An additional test of the model's dependability was performed through residual analysis. The findings show that the mean residual value was very close to zero (0.00000) and the standard deviation measured 0.977 indicating balanced prediction errors with minimal systematic deviation. Several outlier points appeared in the data set, yet the distribution patterns stayed within normal parameters. The distribution pattern of our dependent variable in the histogram was close to normal which validated the homoscedasticity assumption of our model. The Normal P–P Plot analysis demonstrated that error term residuals tracked the diagonal line properly thus verifying error term normality which supported confidence in the regression analysis outcomes.

Conclusion

Research evidence shows how university students' adoption of AI-ChatGPT depends mainly on their scores on Openness to Experience and Conscientiousness personality traits. Based on the study results internal motivations through personality traits prove to have stronger effects than external consideration including perceived ease of use and peer influence when it comes to AI engagement. The impact of Academic Pressure and Technological Awareness factors on the adoption behaviour of students comes between low and moderate yet their absence of statistical significance demonstrates they do not drive adoption decisions primarily. The research findings demonstrate that academic institutions should develop AI integration strategies which match individual personality traits.

Limitations and Future Research

The study contains critical findings although multiple constraints require evaluation and multiple future research directions need attention. Limited sample size of one institution hinders the ability to generalize research results. The study failed to examine deeply how cultural along with geographic and demographic elements affected its results despite being factors possibly shaping the results. The conducted research analysed personality traits and external elements as its main variables while omitting other potentially important aspects including digital competency and faculty practices alongside institutional framework. The research results may be affected by response bias since it depends on self-reported data as well as the inability of the cross-sectional design to track how behaviour changes during different time periods. Upcoming empirical studies need to study a wider range of demographic groups while incorporating more research variables together with tracking behaviour change through time. Research on the field would be enhanced through studies comparing different AI tools as well as studies investigating AI ethics in all their dimensions including academic integrity and creativity. The adoption process of AI-Chat GPT in education requires systematic evaluation of new AI innovations and inclusion of administrators and faculty feedback to establish a complete understanding of this phenomenon.

Notes

1. **Personality Traits** (Venkatesh et al., 2003) Traits like openness and extraversion influence tech adoption. Focus on how these traits affect student use of ChatGPT.
2. **Technology Acceptance Model (TAM)** (Davis, 1989) Perceived ease of use and usefulness drive adoption. Analyze how students find ChatGPT beneficial for their studies.
3. **Social Influence** (Bhattacherjee, 2001) Peer influence affects tech adoption. Examine how student communities impact ChatGPT usage.
4. **Trust and Security** (Liu et al., 2019) Trust concerns hinder adoption. Investigate how students trust ChatGPT in academic settings.

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