JOURNAL OF ACADEMIC RESEARCH FOR HUMANITIES
ISSN 2663-192x

ORCID of JARH: https://orcid.org/0009-0000-0723-9485
DOI Number of the Paper: https://zenodo.org/records/18328351
Link of the Paper: https://jar.bwo-researches.com/index.php/jarh/article/view/589
Edition Link: Journal of Academic Research for Humanities JARH, 5(4) Oct-Dec 2025
HJRS Link: Journal of Academic Research for Humanities JARH (HEC-Recognized for 2024-2025)

BIG FIVE PERSONALITY TRAITS AND UNIVERSITY STUDENTS' MOTIVATION TO USE AI APPLICATIONS: EVIDENCE FROM PAKISTAN

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Paper Information

Citation of the paper:

(JARH) Sahar. F., & Hassan. Z., (2025). Big Five Personality Traits and University Students' Motivation to Use AI Applications: Evidence from Pakistan. In *Journal of Academic Research for Humanities, 5(4), 77-90.*

QR Code for the Paper:

Subject Areas for JARH:

1 Psychology
2 Social Sciences and Humanities

Timeline of the Paper at JARH:

Received on: 30-10-2025.
Reviews Completed on: 16-12-2025.
Accepted on: 25-12-2025.
Online on: 31-12-2025.

Recognized for BWO-R:

HJRS HEC Journal Recognition System

Published by BWO Researches INTL:

BWO RESEARCHES (PVT) LTD INTERNATIONAL

DOI Image of the paper:

DOI 10.5281/zenodo.15649213

Abstract

Artificial intelligence (AI) is becoming increasingly integrated into the educational process of higher education, which is why it is rather significant to comprehend the psychological variables that affect the interaction of students with AI tools. This paper tested the hypothesis that Big Five personality indicators can be used to predict the reasons why university students want to use AI applications, on both academic and personal levels. The study design was a quantitative cross-sectional design guided by the Five-Factor Model and technology adoption frameworks (TAM and UTAUT2). 135 Pakistani students at universities aged 18 to 25 were involved in the study (67 males and 68 females). The participants were asked to fill in the Mini-IPIP and Questionnaire of AI Use Motivation (QAIUM). The analysis of data in Jamovi was done by multiple regression and independent-samples t-tests. Neuroticism had significant predictive validity on lower expectancy ($\beta = -0.252$, $p = .004$) and attainment value (-0.215, $p = .013$), and the predictive validity of more perceived costs of AI use (-0.197, $p = .024$). Extraversion, agreeableness, conscientiousness, and openness were not important predictors of motivation dimensions. Comparisons in gender revealed that the males had greater expectancy ($p = .041$), utility ($p = .014$) and intrinsic motivation ($p = .008$), whereas the females had greater neuroticism ($p = .050$). Overall, the results highlight the importance of emotional stability and gender in designing and implementing AI-based learning support, underscoring the need for emotionally supportive and gender-sensitive AI integration strategies in higher education.

Keywords: Personality, Motivation, Students, AI, Pakistan

Introduction

Artificial Intelligence (AI) is rapidly changing the field of higher education and changes the way students learn, communicate with academic content, and receive educational assistance. Adaptive instruction, individualised feedback, and on-demand support of students have been made possible by the AI tool integration of chatbots, automated tutors, and intelligent learning platforms (Bahroun et al., 2023, Shi, 2023). This has been especially influenced in higher education whereby varying learning needs, cognitive styles as well as motivation patterns have become more pronounced. Although much of the current studies revolve around the effectiveness of AI in enhancing the teaching processes and efficiency in the administration system, much less has been devoted to psychological aspects that influence the desire of students to use AI technologies (Ma et al., 2024; Rane et al., 2023; Yilmaz, 2024). Personality traits are among the psychological factors that can determine the interaction of students with AI. Personality traits are consistent tendencies of cognition, emotion and behaviour that determine the way people react to learning surroundings and technological advancements. The Big Five model of personality has been popular in the study of the differences in academic behaviour, emotional regulation, or the use of technology between individuals based on the five components: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (Marengo et al., 2021; Kara et al., 2024). These attributes have been attributed to creativity, time management, teamwork, coping with stress and using educational technologies. Nonetheless, even with the increased attention to the use of AI, the current literature has seldom studied the role of certain personality traits in motivating the use of AI, specifically in the academic context (Cangir, 2024). It has been established that AI could supplement academic assignments and self-study because it is effective in tailoring learning platforms to the needs of individual learners (Chang and Kidman, 2023; Marouf et al., 2024; Onesi-Ozigagun et al., 2024; David, 2024). Other applications of AI include supporting the efficiency of institutions, e.g., automatic grading, attendance tracking, and predictive analytics to identify at-risk students (Gnanaprakasam and Lourdusamy, 2024; Srinivasa et al., 2022; George and Wooden, 2023). Regardless of these documented advantages, little of the literature has addressed the effects of internal student factors on willingness, confidence, and motivation to use AI tools including personality and emotional tendencies. The studies investigating the connection between personality traits and the use of technology might imply that Openness to Experience positively correlates with curiosity and experimentation, Conscientiousness with efficiency and self-management, Extraversion with social interaction, Agreeableness with cooperation, and Neuroticism with emotional sensitivity and anxiety (Christensen, 2023; Abu Raya et al., 2023; Spielmann et al., 2022; Sharma and Behl, 2022; Scholz et al., 2022;) Wendt et al Nevertheless, the results of different studies are questionable and mostly based on the Western or highly digitised educational environment (Mohseni et al., 2024; Ma et al., 2024; Park and Woo, 2022). Such settings are quite different to those of countries like Pakistan where university education is frequently test-based, the digital infrastructure is disproportional, and AI-based institutional integration is not extensive. The correlation between personality traits and motivation relating to AI may thus have a modifying effect by means of cultural norms, academic pressure, and access constraints. The motivation to utilise AI is a multi-dimensional phenomenon, consisting of such dimensions as expectancy, attainment value, utility value, intrinsic interest, and perceived cost. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) are technology adoption frameworks that have highlighted these motivational elements as fundamental contributors to technology adoption

(Worthington, 2021; Barz et al., 2024; Mohamed Hashim et al., 2022). Although these models have been associated with affecting external and context factors as it relates to technology use, they do not take into consideration personal psychological variables that define the motivational beliefs of students. Having personality psychology merged with motivational frameworks could consequently give a better comprehension of the reasoning behind students using or being uninterested in using AI tools. This gap will be addressed in the present study that focuses on the extent to which Big Five personality traits predict the disposition of university students to use AI applications in academic and personal settings. It examines the correlation between personality traits and five dimensions of motivation, which are expectancy, attainment value, utility value, intrinsic interest, and perceived cost. This study is a culturally based quantitative, cross-sectional study that provides a validated psychometric measure of AI motivation among Pakistani university students in an educational setting that is underrepresented in the literature. It is a unique study since it goes beyond the overall attitudes towards AI by incorporating the personality factor, motivation levels, and gender variations. The findings will be informative about psychologically sensitive, gender-responsive, and culturally suitable methods to integrate AI into higher education by determining the emotional and demographic factors that drive AI engagement.

Goals of the Study:

1. To test the hypothesis of whether the Big Five personality traits are predictive of university students' motivation to use AI applications in universities.
2. To examine the connection between personality factors and various motivational aspects of AI application such as expectancy, value, interest, and perceived cost.
3. To investigate the gender discrepancy in personality traits and AI-based motivation in university students.

Research Questions:

1. What are the Big Five personality characteristics that are associated with student motivation to use AI application in higher education?
2. What is the relationship between Big Five personality traits and various dimensions of motivation of AI use?
3. Do there exist notable differences between genders in personality traits and the desire to use AI applications?

Innovation and Contribution:

The research is relevant to literature because:

1. Combining higher education and AI motivation with personality psychology.
2. Using psychometric tools (Mini-IPIP and QAIUM) to study the psychological predictors of AI use.
3. Giving empirical data of Pakistan, another underrepresented non-Western educational scenario.

Regardless of the increasing amount of research regarding the AI adoption into higher education, most available research focuses on the technical and usability and performance-based aspects of AI adoption through the frameworks of TAM and UTAUT2. Although these models describe the overall patterns of acceptance, they do not pay significant attention to the personal psychological and emotional peculiarities, which define the interest of students in working with AI tools. Specifically, such personality traits, as well as affective dispositions, like emotional stability, have not been studied in terms of AI adoption. In addition, little empirical evidence on the topic exists in developing and non-Western educational settings such as Pakistan. Since the culture in Pakistan is examination-based, digital infrastructure is not even, and institutional adoption of AI is not high, the motivational processes might be significantly different in the West. The current paper fills this gap by evaluating how the Big Five personality traits relate to several AI use motivation dimensions in Pakistani university students and therefore provides a psychologically and culturally knowledgeable approach to the issue of AI adoption in higher education.

Literature review and data collection

Artificial Intelligence in Education

Artificial intelligence (AI) has become increasingly embedded in higher education, influencing both teaching–learning processes and institutional operations. AI-based technologies, including intelligent tutoring systems, adaptive learning platforms, and virtual assistants, enable personalised feedback, adaptive instruction, and real-time academic support (Chang & Kidman, 2023; Marouf et al., 2024; Shah et al., 2024). These systems can identify learning gaps, monitor student progress, and provide targeted recommendations, thereby enhancing engagement and learning effectiveness (Onesi-Ozigagun et al., 2024). Conversely, chatbots and virtual assistants based on AI can facilitate the education process by answering academic questions, helping students with homework, and performing other activities that could enhance their learning effectiveness and persistence (David, 2024).

In addition to instructional support, AI has also helped in efficient administration and evaluation in higher education. The automated systems of grading and feedback can lower the workload of instructors and provide instructors with timely and consistent feedback, which is why they can concentrate on more interactive and student-centred teaching methods (Gnanaprakasam and Lourdusamy, 2024). Through institutional use like attendance checking and electronic tracking, other routine processes are also simplified (Srinivasa et al., 2022). Moreover, predictive analytics has also applied to predicting academic at-risk students to provide early interventions by means of tutoring, mentoring, or counselling programs (George and Wooden, 2023). All these innovations demonstrate the growing use of AI in academic and institutional life.

Although the findings regarding AI, as far as it can be used to increase efficiency and learning outcomes, are substantial, the bulk of the current research focuses on technological ability and performance-oriented results instead of psychological processes that influence the engagement of students. Notably, the use of AI tools does not have an equal impact on students. Some think that AI will make things more professional and helpful, whereas others feel scared, nervous, or opposed to the use of AI technologies. Other related studies have also expressed the issue of student dependence on AI tools in higher education, pointing to the effect of psychological variables like academic self-efficacy and stress on AI use (Umm e et al., 2025). The differences cannot be entirely attributed to access or technical skills, and it is said that motivation and emotional aspects are vital in developing AI engagement. In turn, the introduction of AI into the world of higher education must be viewed not as a technological shift but as a psychologically motivated phenomenon that depends on personal differences and emotional requirements.

Moreover, many of the previous studies were conducted in the educational setting where AI integration is institutionalized and backed with infrastructure and training. Conversely, when an AI application is informal or self-directed, students might have to navigate AI applications on their own, which could raise the variability of confidence, emotional readiness and perceived challengingness. These contextual variations are important to highlight the significance of analyzing the psychological determinants of AI motivation, especially when institutional support of AI is scarce.

Big Five Personality Traits and Technology Use

Personality traits are patterns of thinking, feeling and behaviour that are relatively constant and determine how individuals interact with learning environments and technology. Big Five personality framework, which consists of Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, has been extensively used in educational psychology to clarify the differences between individuals in terms of academic engagement, emotional regulation, and technology-related behaviour (Marengo et al., 2021; Kara et al., 2024). All characteristics represent unique psychological inclinations that can potentially affect the motivation of students to consider and use AI-based tools in higher education.

Openness to experience is defined by curiosity in the mind, imagination, and the desire to learn new things. Educational space in technologically supportive space, research has tended to associate openness with positive attitudes to innovation and the use of technology exploration, including AI systems (Abu Raya et al., 2023; Mohseni et al., 2024; Ma et al., 2024). Yet, this relationship seems to be circumstantial. The experimentation opportunities could be constrained in a rigorous or examination-focused curriculum, which can lead to the motivation impact of openness on AI use to be diluted.

Conscientiousness is self-discipline, organisation, goal-directed behaviour, and has always been related to academic performance and successful self-management (Spielmann et al., 2022). Good students can be encouraged to embrace technology that can result in increased output and efficiency, especially where the technology fits the school demands (Menon, 2024). However, it is essential to note that once AI tools are not officially introduced as part of coursework or assessment, responsible students will view the latter as redundant or even dangerous, which would inhibit the latter.

Extraversion is linked with outgoingness, aggressiveness, and exterior incitement. Extraverted learners are more likely to like interactive and collaborative learning experiences and would be interested in AI-based tools that can provide communication and feedback, e.g., chatbots or interactive platforms (Sharma and Behl, 2022; Ma et al., 2024). Nevertheless, in the case with AI applications when they are mostly utilised to do individual tasks, including summarisation or grammar correction, extraversion might be less relevant, which makes sense in the context of the functionality of tools to moderate personality effects.

Agreeableness is a quality of cooperation, empathy, and positive attitude towards peaceful social relationships (Scholz et al., 2022). Although agreeable people can be open to technologies that enhance teamwork and positive feedback (Kallianou, 2024), in collectivistic and teacher-centered learning settings, agreeableness can be complied with instead of being proactive. Consequently, students who are amicable might not want to be independent in adopting AI tools unless this application becomes institutionalised or recommended.

The personality trait of neuroticism, which is emotional unpredictability, anxiety and sensitivity to stress, has displayed unequal relations with technological use. According to some researchers, neurotic individuals are likely to avoid technology because of fear of failure or low self-efficacy, whereas other researchers state that AI can be applied as coping strategies to overcome academic stress and uncertainty (Lee et al., 2021; Wendt et al., 2023). This duality implies that neuroticism is potentially a determining factor of both AI usage among students and their perceptions of its motivational advantages and psychological costs and especially in high-stress academic settings where emotional support is less developed.

It is important to note that much of the current research on the correlation between personality traits and the use of technology has been inspired by Western or highly digitised education (Park & Woo, 2022). These settings differ substantially from developing educational systems, where access to AI tools, institutional support, and pedagogical practices vary widely. Cultural, infrastructural, and institutional factors may therefore moderate the motivational influence of personality traits on AI use, highlighting the need for context-specific research.

Motivations for AI Use

Motivation to use AI applications is inherently multidimensional, encompassing cognitive beliefs, emotional responses, and perceived costs. Technology adoption models such as the Technology Acceptance Model (TAM) (Figure 1) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Figure 2) have been widely employed to explain technology-related behaviour in educational settings (Worthington, 2021; Barz et al., 2024; Mohamed Hashim et al., 2022). TAM emphasises perceived usefulness and perceived ease of use as key determinants of adoption, while UTAUT2 extends this framework by

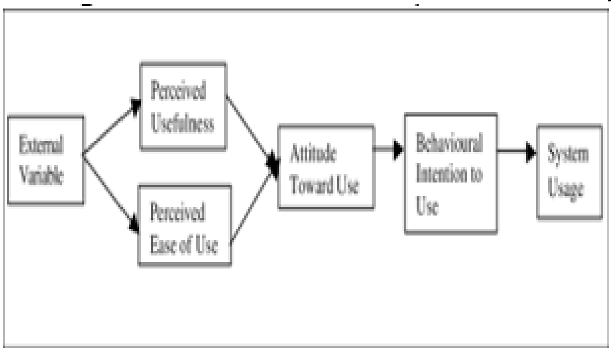
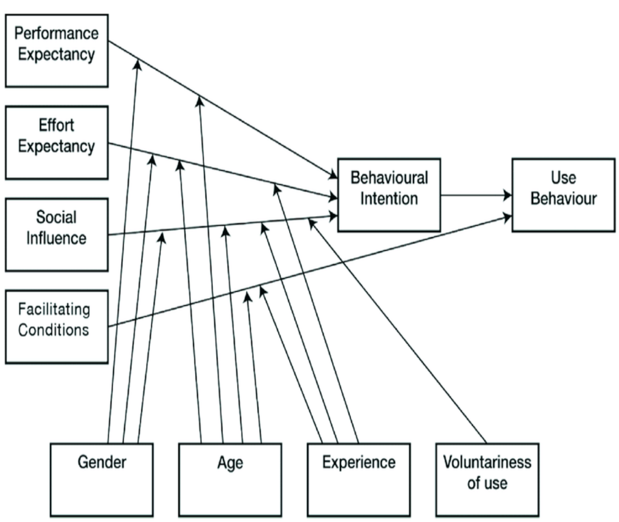


Figure 2

The Unified Theory of Acceptance and Use of Technology (UTAUT2)

It depicts the effect of performance expectancy, work expectancy, social influence, and facilitating condition on the behavioural intention and use behaviour. The strength of these relationships is influenced by moderating variables that include gender, age, experience and voluntariness of use.



Although these models demonstrate strong explanatory power in digital learning contexts, they primarily reflect rational evaluations of technology and provide limited insight into emotional and motivational differences among incorporating constructs such as performance expectancy, hedonic motivation, habit, and perceived cost.

Figure 1

The Technology Acceptance Model (TAM)

This theory formulated by Davis (1986), shows the relationship between the usefulness of a system and the ease of using the system and how the users develop behaviours depending on the attitude that they have towards the system. users. In educational psychology, motivation is more comprehensively conceptualised through expectancy–value theory, which considers students' beliefs about success (expectancy), perceived importance (attainment value), usefulness (utility value), enjoyment (intrinsic interest), and perceived cost. The dimensions provide a subtle system of thought on why students use or do not use AI.

These motivational constructs are operationalised in the Questionnaire of AI Use Motivation (QAIUM), which allows a comprehensive evaluation of AI related motivation outside of the traditional acceptance scales. Notably, psychological attributes influence inspirational ideologies. Students who are emotionally stable or those who are novelty-oriented can see AI as valuable and interesting, but those who have anxiety or self-doubt can concentrate on the perceived difficulty or the psychological cost. Although these relationships are theoretically supported, empirical studies that investigate the relationship between personality traits and certain motivational aspects of AI use are scarce especially in tertiary education and in non-Western cultures.

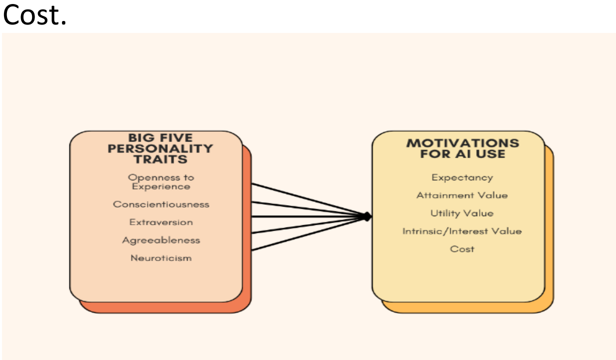
In addition, motivational processes are likely to be affected by institutional support, pedagogical norms and cultural expectations. Students might need more inner motivation and emotional readiness to interact with AI in the context of educational settings in which the use of AI tools has no formal basis. This indicates that the motivation of AI can be best explained by balancing between the models of technology adoption and psychological understanding. The current study provides a psychologically grounded framework of understanding AI adoption in higher education by applying expectancy, attainment value, utility value, intrinsic interest, and perceived cost about personality traits and filling gaps in the current technology-centered theories. Higher education contexts also present qualitative data that indicate that emotional reactions to AI are both positive and negative, as some students view AI as a creative boost, and others see it as a constraint or uncomfortableness, which supports the relevance of affective and motivational dimensions in the adoption of AI (Shahid, M. M., 2025).

Based on the reviewed literature, the present study proposes a conceptual framework linking Big Five personality traits to multiple motivational dimensions of AI use in higher education (Figure 3).

Figure 3

Conceptual Framework Linking Big Five Personality Traits to AI Use Motivation

Theoretical model of the effect that Big Five personality traits have on motivational aspects of university students to use AI-based applications. The five traits Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism have been postulated to affect certain dimensions of motivation, namely Expectancy, Attainment Value, Utility Value, Intrinsic/Interest Value and Cost.



Methodology

This study employed a quantitative, cross-sectional research design to examine whether Big Five personality traits predict university students' motivation to use artificial intelligence applications. Data were collected from undergraduate students enrolled in Pakistani universities using validated self-report instruments measuring personality traits (Mini-IPIP) and AI use motivation (QAIUM). Multiple regression analyses and independent-samples t-tests were conducted using Jamovi to address the study's research questions.

Research Design and Participants

The current study used quantitative and cross-sectional correlational research to test the association between the Big Five personality factors and the motivations of university students to utilize artificial intelligence applications. This design is deemed to have been suitable since the major aim was to find out patterns of association and predictive links among naturally occurring psychological variables, as opposed to being able to establish cause and effect. Personality traits and motivational beliefs are fixed constructs which are independent of manipulation by the researcher, and an experimental design cannot be adopted in the current study objectives. The method of cross-sectional research made it possible to gather data at one point in time, which is an effective way of gathering psychological traits of students and their motivational dispositions to using AI in their existing academic settings. This method is frequently applied to educational and psychological studies when the researcher aims to study personal differences and attitudes towards technology, especially in situations where it might be infeasible to collect longitudinal data. The respondents were full-time undergraduate university students who were studying in higher institutions in Pakistan. The sample size of the study was 135 students (67 males and 68 females), aged between 18 and 25 years ($M = 21.3$, $SD = 2.5$). The sample students represented various academic fields of study, which enabled learning more about the motivation of AI in various areas of study. The purposive sampling was used to guarantee the selection of the participants according to the criteria outlined in the inclusion: the respondents had to be full-time university students between the ages of 18 and 25 and included in the academic environment. G Power 3.1 was used to determine the sample size to ensure that there was sufficient statistical power to carry out multiple regression analyses. The analysis showed that at least 138 participants were needed to identify a medium effect size with enough power. Despite 138 responses collected initially, three cases were ruled out of the sample at the screening of data because of statistical outliers, and the final sample of 135 participants was selected. This was considered an adequate sample, considering the intended tests and corresponds with the suggested requirements on regression research studies in psychology.

Measures

The two standardized psychometric tools that were used in the research to measure the key constructs of interest, that is, personality traits and AI use motivations, were used. The two measures have found significant application in psychological and educational studies and have been shown to possess satisfactory psychometric characteristics, hence are appropriate to the purpose of the current study. The administration of all the instruments was in the form of an online survey that was in English.

Big Five Personality Traits

The Mini International Personality Item Pool (Mini-IPIP), a short 20-item self-report scale, was used to measure the personality traits based on the five dimensions of the Big Five model of personality: Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (Donnellan et al., 2006). The four items used to measure each of the dimensions of personality give a brief but sound evaluation of consistent personality traits. The respondents have answered all the items on a five-point Likert scale, starting with 1 (Strongly Disagree) and ending with 5 (Strongly Agree). Many points on each subscale denote that the personality trait portrayed is more expressed. The Mini-IPIP was chosen because of its efficiency, good psychometric validity and its applicability in online surveys, especially in studies involving student populations in which length and fatigue of the participants are major issues of concern. The studies conducted in the past have shown that the Mini-IPIP has acceptable internal consistency and construct validity with various samples to use it as a credible indicator of personality traits. The examples used are I have a vivid imagination (Openness), I get chores done right away (Conscientiousness), I am the life of the party (Extraversion), I sympathize with other people (Agreeableness), and I have frequent mood swings (Neuroticism). The subscale scores were computed by adding the responses of the items to each trait, with higher scores indicating the intensity of a trait.

Motivations for AI Use

The motivations to use AI applications were measured by the questionnaire of AI Use Motivation (QAIUM) because the questionnaire was developed by the authors to gauge the motivational orientation of students towards the use of AI in education (Yurt and Kasarci, 2024). The design of the QAIUM was developed in a way that allows the measurement of different dimensions of the AI-associated motivation to provide a more accurate assessment as compared to the generic technology acceptance measures. The scale has five items that are rated using a five-point Likert scale (1 Strongly Disagree to 5 Strongly Agree) and measures five motivational dimensions that comprise expectancy, attainment value, utility value, intrinsic interest and the cost perceived. The ability to successfully use AI applications is called expectancy, the value of the ability to learn AI-related capabilities is called the attainment value, the value of how useful AI can be in academic performance and productivity is called utility, enjoyment and curiosity in using AI applications is called intrinsic interest, and the cost of using AI applications is called perceived cost. The expectancy, attainment value, utility value, and intrinsic interest subscale scores are applied to demonstrate that the individual is more motivated to use AI, whereas the cost subscale scores are applied to demonstrate that a person perceives more barriers or obstacles. The QAIUM has established a decent internal consistency of all the subscales and the coefficients of reliability that are reported to be even greater than the accepted levels. Its concern with motivation and the fact that it is not dependent on the frequency of use also contribute to its special applicability to investigate the psychological variables which can determine the use of AI among students at a university.

Data Collection Procedure

Data collection was carried out with the help of an online survey following the ethical approval that had been made by the respective institutional review board. The questionnaire was designed and carried out with the assistance of Microsoft Forms. The platform is safe and comfortable, and can be utilized to collect psychological data concerning the student population. The recruitment materials contained the purpose of the study, eligibility and voluntary participation and were posted on online platforms which are commonly visited by students in the university. Once in the survey, the participants were informed of an informational sheet on the purpose of the study, the procedures, as well as the expected duration of the study and the protection of the ethical issues. The subjects were informed that they had the free will to take part in the study and they could withdraw from the study at any time before they could be asked to provide their responses. The participants were then subjected to the surveys after having been informed through the consent form, which they had been provided with electronically. The questionnaire began with the short demographic section, which took into consideration age, gender and academic background. No information that was obtained was used to identify the participants; it was obtained to preserve the anonymity of the participants. The subjects were then expected to go through the Mini-IPIP personality measure and the Questionnaire of AI Use Motivation (QAIUM). It was stable and well-instructed in each section to enable quality and careful answers. The questionnaire required a period of about 15-20 minutes to complete. The debriefing statement was displayed at the end of the survey so that the participants could restate the purpose of the research and contact details of the researcher if the participants had any questions or concerns. All data was put in a safe place in files which were secured with passwords and only accessible to the researcher and supervisor. The steps that were done during the processing of data were ethically considered in relation to confidentiality, anonymity and data protection, and all the data obtained is going to be stored for a certain duration before secure erasure according to the demands of the institution.

Results

This section provides statistical results exploring the degree to which Big Five personality factors determined the desire of university students to use the AI applications. The analyses were performed in terms of multiple linear regression and independent-samples t-tests. All assumptions for parametric testing were assessed and met before analysis. Overall, the results indicate that Neuroticism was the only Big Five personality trait that consistently predicted motivation-related dimensions of AI use. Higher levels of Neuroticism were associated with lower expectancy and attainment value and with higher perceived cost, while the remaining personality traits did not show significant predictive effects. Gender differences further revealed higher AI-related motivation among male students and higher perceived cost among female students.

Descriptive Statistics

All personality traits and motivational dimensions were described according to 135 valid responses. The mean scores of the participants with respect to all the five traits of the Big Five were moderate with Openness ($M = 12.4$, $SD = 2.82$), Conscientiousness ($M = 12.1$, $SD = 2.80$), Extraversion ($M = 12.7$, $SD = 3.26$), Agreeableness ($M = 13.7$, $SD = 2.73$), and Neuroticism ($M = 12.4$, $SD = 3.01$). Regarding the

AI-related motivations, Utility Value (M = 16.1, SD = 2.75) followed by

Intrinsic Motivation (M = 15.5, SD = 2.81), then Attainment Value (M = 15.3, SD = 2.96), Expectancy (M = 15.1, SD = 2.96), and finally Cost (M = 14.9, SD = 2.94) had the highest mean scores.

Table 1:
Descriptive Statistics of Personality Traits and AI Motivation

Variable	N	Mean	SD	Minimum	Maximum
Extraversion	135	12.7	3.26	7	20
Agreeableness	135	13.7	2.73	7	20
Conscientiousness	135	12.1	2.80	6	18
Neuroticism	135	12.4	3.01	4	20
Openness	135	12.4	2.82	6	20
Expectancy	135	15.1	2.96	6	20
Attainment Value	135	15.3	2.96	6	20
Utility Value	135	16.1	2.75	8	20
Intrinsic Interest	135	15.5	2.81	8	20
Perceived Cost	135	14.9	2.94	7	20

Regression Analyses

Multiple linear regression was done on five distinct models to determine the prediction of each dimension of motivation by the Big Five personality traits. The Expectancy predictive model was not found to be statistically significant in general, $F(5, 129) = 2.20$, $p = .059$, $R^2 = .079$. Nonetheless, Neuroticism was a strong negative predictor (2 = -0.252, p =.004). Other personality variables were not significant predictors of expectancy. Attainment Value model was statistically significant, $F(5, 129) = 2.34$, $p = .046$, $R^2 = .083$. Once again, neuroticism was a major negative predictor (0.215, p =.013), whereas Openness, Conscientiousness, extraversion, and agreeableness were not significant predictors. The regression equation of Utility Value was not statistically significant, $F(5, 129) = 1.92$, $p = .092$, $R^2 = .040$. No Big Five attributes were found to be significant predictors of perceived AI applications' utility. The model that predicted Intrinsic Motivation was also not significant, $F(5, 129) = 0.31$, $p = .902$, $R^2 = .012$, which means that personality traits were not significant in predicting enjoyment motivation to use AI. Likewise, the model that predicts Perceived Cost in general was not statistically significant, $F(5, 129) = 1.41$, $p = .220$, $R^2 = .052$. However, the perceived cost was highly predicted by Neuroticism (=-0.197, p=.024).

Gender Differences

The independent-samples t-tests were used to compare the differences between genders regarding personality characteristics and AI-related motivations. The mean of Female students was also considerably greater than that of males on Neuroticism, $t(133) = 1.98$, $p = .050$. There were no other personality differences that were significantly different between the genders. Expectancy, $t(133) = -2.07$, $p = .041$, Utility Value, $t(133) = -2.49$, $p = .014$, Intrinsic Motivation $t(133) = -2.68$, $p = 0.008$, were significantly higher with male students. The perceived Cost of using AI was found to be much higher among females, $t(133) = -4.01$, $p < .001$.

Discussion

This study examined whether Big Five personality traits predict university students' motivation to use artificial intelligence applications and whether gender differences exist in personality traits and AI-related motivation within a Pakistani higher education context.

Summary of Key Findings

The findings indicate that Neuroticism was the only personality trait consistently associated with AI-related motivation. Higher levels of Neuroticism were linked to lower expectancy and attainment value and to higher perceived cost of AI use, suggesting reduced confidence and greater emotional burden when engaging with AI tools. In contrast, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience did not significantly predict any motivational dimensions. These results suggest that emotional and contextual factors may play a more influential role in shaping AI-related motivation than broad dispositional personality traits in this setting.

Role of Neuroticism in AI Motivation

The significant percentage of Neuroticism as a predictor emphasizes the role of emotional stability in the involvement of AI applications among students. Because of their high levels of Neuroticism, such students have a higher tendency to get anxious, stressed, and doubtful, which can lower their confidence in effectively utilizing AI tools and make engagement seem more expensive psychologically. Where emotional support is less than expected in performance-driven academic settings, AI tools are also cognitively stimulating or even harmful instead of helpful. It is interesting to note that Neuroticism has only affected the beliefs on motivation, and not the tendency of simple usage, reducing expectancy and attainment value, with increasing costs perceived. This trend highlights the emotional character of the AI motivation and implies that emotional reactions might become more significant than the rational consideration of usefulness in determining the likelihood of students using AI.

Non-Significant Big Five Personality Traits

The lack of meaningful differences in Openness, Conscientiousness, Extraversion, and Agreeableness indicates that personality factors that are generally attributed to learning experience and technology adoption are not necessarily universal in terms of education. The reason could be that AI tools are not explicitly integrated into the curriculum or assessment frameworks, which restricts the roles of such characteristics as curiosity, self-discipline, or sociability in transforming into a motivational activity. Such dispositional tendencies might be dormant without institutional reinforcement, and consequently, their effect on AI-related motivation can be less pronounced. This observation contrasts with other studies that have been done in highly technological or student-centred learning institutions and environments, where such characteristics will tend to predict the positive technology adoption behaviour.

Gender Differences in AI Motivation

The existence of gender differences also presents the influence of emotional and socio-cultural factors in the engagement with AI. Male students indicated a greater expectancy and utility value as well as intrinsic motivation, indicating more confidence and pleasure in the use of AI tools. Female pupils, conversely, were more Neurotic and perceived cost, meaning that their emotional burden and anxiety around AI usage were higher. These disparities can be in terms of differences in socialization, access to technology and even previous exposure and not just in natural ability. In this regard, the AI integration strategies should not presuppose an equal level of emotional preparedness of both genders but must be taken in a gender-sensitive manner that would accommodate confidence-building and anxiety reduction strategies.

Cultural and Institutional Context

The results should be discussed in the framework of Pakistani higher education, in which learning based on examinations, underdeveloped institutional integration of AI, and unequal digital access are widespread. Depending on the conditions, emotional preparedness and confidence can be more influential in shaping motivation related to AI than dispositional qualities. This situational fact can be used to justify the fact that the personality traits that are generally connected with proactive technology use were not found to be important predictors. Further, the findings indicate that conventional technology acceptance models like TAM and UTAUT2 might be constrained when used without regarding emotional and cultural factors. The inclusion of affective constructs in the framework of AI adoption potentially offers a more precise definition of student motivation in non-Western and resource-limited education, though.

LIMITATIONS AND FUTURE RESEARCH

Although it has contributed to it, this study has several limitations. The cross-sectional design does not allow causal interpretation of the relationships that exist between personality traits and AI motivation. The use of self-report measures can also create bias in responses and cannot adequately reflect the real use behaviour of AI. The sample also included undergraduate students at urban universities in Pakistan, which restricts the ability to apply the results to other levels and settings of education. Further studies are advised to use longitudinal and mixed methodology, including behavioural consequences of AI use, other psychological variables, and cross-cultural comparisons to enhance the knowledge of the emotionally and culturally informed AI adoption in higher education.

Conclusion

This study examined the role of Big Five personality traits in predicting university students' motivation to use artificial intelligence applications in higher education within the Pakistani context. The findings demonstrate that Neuroticism was the only personality trait that consistently influenced AI-related motivation, negatively affecting expectancy and attainment value while increasing perceived cost. In contrast, other personality traits did not show significant predictive effects. Gender differences further revealed higher AI-related motivation among male students and greater emotional burden among female students.

From a theoretical perspective, this research contributes to educational psychology and AI adoption literature by extending traditional technology acceptance models through the integration of personality psychology and expectancy–value motivation theory. The results suggest that emotional stability plays a more central role than broad dispositional traits in shaping motivation toward AI use, particularly in examination-oriented and resource-constrained educational settings.

Practically, the findings highlight the need for emotionally supportive and gender-sensitive AI integration strategies in higher education. Universities and instructors should prioritize AI literacy initiatives that build confidence, reduce anxiety, and address perceived psychological costs, especially for emotionally vulnerable students. Policymakers may use these insights to design psychologically informed AI training frameworks that promote equitable and effective engagement with AI technologies.

Despite its contributions, the study is limited by its cross-sectional design, reliance on self-report measures, and context-specific sample. Future research should adopt longitudinal and mixed-method approaches, incorporate behavioural indicators of AI use, and explore additional psychological and contextual factors across diverse cultural settings to further advance understanding of personality-driven AI motivation in higher education.

Recommendations

Emotionally supportive AI tools should be embraced in universities to alleviate anxiety and develop confidence among students. The training programs must be aimed at enhancing the AI self-efficacy by using low-pressure learning settings. It is suggested to implement gender-responsive AI literacy programs to narrow the confidence gap, and policymakers need to implement AI more strategically in the curricula to foster equity of access and incentives.

Innovation / cutting-edge research

The study is novel by merging personality psychology and models of motivation towards AI adoption. It is also one of the pioneers to analyze the predictability of Big Five traits on various motivational aspects of AI usage in a Pakistani higher-education setting, taking into consideration the potential of emotional and cultural variables that have frequently been neglected in the study of technology acceptance.

Research location

The study was carried out in Pakistan among undergraduate learners of higher institutions of learning in the urban areas where different disciplines were represented. The data was gathered on-line indicating an authentic experience of students in their academics without the intervention of the institution.

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