Building Trust in Artificial Intelligence: Personality-based Strategies to Enhance Student Engagement in Higher Education

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***Abstract*—As generative artificial intelligence becomes more integrated into educational environments, comprehending the psychological traits influencing users' engagement with these technologies is crucial. This study investigated the influence of personality traits on the self-reported use of ChatGPT and the mediating role of trust in this relationship by drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework as a theoretical reference. Employing a quantitative research design, data were collected through structured questionnaires administered to a sample of 330 university students in North Cyprus using purposive/judgmental technique. The data were analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM). The findings show that extraversion and conscientiousness did not significantly influence perceived trust, whereas agreeableness, neuroticism, and openness are significant predictors of trust. In addition, perceived trust has a significant positive effect on ChatGPT use, highlighting its pivotal role as a cognitive evaluation linking dispositional traits to behavior. These results underscore how individual differences contribute to technology adoption and offer practical insights for educators and platform developers seeking to foster trustworthy Artificial Intelligence (AI) experiences. In an era of rising technological awareness, understanding the psychological antecedents of trust can help higher education institutions design interventions that encourage responsible and effective use of generative AI tools.**

***Keywords*—big five personality traits, higher education, ChatGPT adoption, student engagement, Trust in Artificial Intelligence (AI), Unified Theory of Acceptance and Use of Technology (UTAUT)**

I. Introduction

A significant change in the digital landscape and the field of Human-Computer Interaction (HCI) has been brought about by the introduction of Generative Pre-trained Transformer (ChatGPT), a sophisticated interactive Artificial Intelligence (AI) developed by OpenAI [1]. Following its November 2022 release, ChatGPT experienced unprecedented public adoption, reaching 100 million users within two months [2]. Its ability to generate contextually relevant and coherent text-based responses stems from its advanced natural language processing capabilities. Due to its rapid diffusion, ChatGPT is widely regarded as a transformative innovation, particularly within Educational Technology (EdTech) and Information Systems (IS) [3]. Its functionalities include facilitating individualized learning experiences, dynamically adapting instructional materials, providing immediate feedback, and supporting administrative tasks, thereby offering considerable benefits in higher education contexts [4]. By extending academic support beyond traditional classroom boundaries, ChatGPT has become an important intellectual resource for students worldwide [5].

Despite the generally positive reception of AI chatbots in education, their rapid deployment has raised critical questions concerning user engagement, acceptance, and associated ethical considerations [6]. Prior research highlights productivity, efficiency, and ethical implications as central themes shaping users' perceptions of ChatGPT [7]. While these studies underscore the growing prevalence of AI technologies and the challenges that accompany their use, a deeper understanding of the psychological factors influencing individual adoption and sustained use remains necessary.

In particular, empirical research examining how individual personality traits shape ChatGPT usage and the role of trust in this relationship remains limited. The Big Five Model of Personality, encompassing Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness, is a well-established psychological framework for predicting user behavior across diverse technology adoption contexts [8]. However, its specific association with trust formation in conversational AI systems is still insufficiently explored. Trust is widely recognized as a critical determinant of effective and sustained technology adoption, yet limited empirical attention has been given to how trust interacts with stable personality characteristics in the context of generative AI. Understanding these interactions is not only essential for enhancing user experience but also for informing the design of AI systems that can mitigate risks related to over-reliance, misinformation, and ethical misuse.

Accordingly, this study examines the influence of Big Five personality traits on the self-reported use of ChatGPT, with trust conceptualized as a mediating mechanism in this relationship. Accordingly, this study examines the influence of Big Five personality traits on the self-reported use of ChatGPT, with trust conceptualized as a mediating mechanism in this relationship. The present study reference Unified Theory of Acceptance and Use of Technology (UTAUT) as a contextual framework to situate the role of trust and individual differences within the broader technology adoption literature. By focusing empirically on personality traits and trust, this study addresses an important gap in existing research on generative AI adoption in higher education. By focusing empirically on personality traits and trust, this study addresses an important gap in existing research on generative AI adoption in higher education.

The findings of this study offer meaningful insights into user behavior that can inform personalization strategies,

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guide future AI design approaches, and support the responsible and ethical application of AI technologies. The remainder of the paper is structured as follows: Section II presents the literature review and hypothesis development. Section III outlines the methodological approach, Section IV reports the data analysis and results, Section V discusses the findings, and Section VI concludes the paper by highlighting theoretical and managerial implications and directions for future research.

II. Literature Review

This study draws on the Big Five Personality Traits framework and established technology acceptance theories to examine individual differences in trust formation and ChatGPT usage behavior. While prominent technology adoption models such as the Technology Acceptance Model (TAM) and the UTAUT primarily emphasize technological and system-related determinants of adoption [9], they tend to give limited attention to stable individual differences and external psychological influences that may shape user behavior [10]. In contrast, the Big Five Personality Traits framework provides a complementary perspective by explaining how enduring personality characteristics influence individuals' perceptions, trust, and engagement with emerging technologies such as ChatGPT. By situating personality-driven trust formation within the broader technology adoption literature, this study seeks to make a meaningful contribution to ongoing discussions of generative AI use, particularly in higher education.

A. The Big Five Personality Traits Framework

The Big Five model comprises five broad personality dimensions: extraversion, agreeableness, conscientiousness, neuroticism, and openness to new experiences [11]. These traits are widely recognized as influential factors shaping how individuals perceive, evaluate, and adopt new technologies [12]. Openness, for instance, is characterized by curiosity, creativity, and a willingness to embrace novel ideas [13]. Individuals with higher levels of openness are more inclined to experiment with innovative tools such as ChatGPT, perceiving them as valuable resources for learning enhancement and creative exploration [14].

Conscientiousness reflects diligence, organization, and a strong sense of responsibility [15]. Conscientious individuals tend to value efficiency and reliability; consequently, they may be more inclined to use ChatGPT when it is perceived as a dependable tool that enhances productivity and task performance [16]. Their engagement with ChatGPT is therefore often deliberate and goal-oriented.

Extraversion is associated with sociability, assertiveness, and positive emotionality [17]. Given that ChatGPT offers interactive features that can simulate conversational exchange, extraverted individuals may be more likely to engage with the system for communication-oriented activities such as drafting messages, participating in dialogues, and engaging in creative storytelling [18, 19].

Agreeableness reflects interpersonal orientation and tendencies toward cooperation, empathy, and trust [20]. Individuals high in agreeableness are typically warm, altruistic, and compassionate, and these characteristics may predispose them to view conversational AI systems more favorably, particularly when trust and ethical considerations are salient [21].

Neuroticism, characterized by emotional instability and sensitivity to negative stimuli, may exert a more complex influence on ChatGPT adoption [22]. Individuals with higher levels of neuroticism may exhibit hesitation or skepticism toward AI systems due to concerns related to reliability, uncertainty, or potential negative consequences [23]. These concerns highlight the importance of trust as a central psychological mechanism influencing AI use decisions.

B. The Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT developed by Venkatesh *et al.* [24], synthesizes key elements from several prominent technology acceptance models to provide a comprehensive framework for understanding technology adoption behavior [25, 26]. UTAUT identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as core determinants of technology use and has been widely applied across diverse technological domains, including electric vehicles, electronic health technologies, artificial intelligence applications, and the Internet of Things [26, 27]. In educational contexts, UTAUT has also been widely used to examine the adoption of educational technologies, such as e-learning platforms, mobile learning systems, and educational chatbots [28].

In the present study, UTAUT is not empirically tested but is instead employed as a contextual reference framework to situate ChatGPT usage within the broader technology adoption literature. Recent research emphasizes that trust plays a particularly critical role in AI and autonomous systems, especially when algorithmic outputs influence or support decision-making processes [29]. Building on this insight, the current study focuses empirically on how personality traits shape trust in ChatGPT and how trust, in turn, influences self-reported usage behavior, thereby complementing established acceptance frameworks without directly modeling their constructs.

C. Perceived ChatGPT Trust

In interpersonal interactions, trust is characterised as "the readiness of one party to be vulnerable to the actions of another party, predicated on the expectation that the latter will undertake a specific action significant to the trustor, regardless of the capacity to oversee or regulate that party" [30]. Furthermore, it is a recognised fact that beliefs about trustworthiness are substantially affected by judgements of the trustee's competence, benevolence, and integrity. Nonetheless, confidence in machines, computers, and AI systems diverges from interpersonal trust. The study concludes that more suitable trusting beliefs in human-technology interactions are efficiency and usability (rather than ability), helpfulness (rather than benevolence), and precision and accuracy (rather than integrity) [31]. The inclination to trust (synonyms: trust propensity, interpersonal propensity to trust) significantly influences behavioural intentions and actual conduct [32]. Accordingly, perceived trust in ChatGPT, defined as the belief in the system's reliability, accuracy, and ethical alignment, is introduced as a mediator between personality traits and usage behaviour.

D. ChatGPT Use

ChatGPT, developed by OpenAI, is a generative AI chatbot that produces coherent, human-like text from user input [33]. The technology has become widely available and used since its introduction in late 2022, sparking curiosity and concern about its potential effects on a variety of industries, including education [34, 35]. By encouraging critical thinking, writing, and AI literacy, ChatGPT offers chances to improve teaching, learning, and evaluation in higher education [36]. According to recent studies, ChatGPT can be used for a variety of educational purposes, including creating tasks, assisting with essay writing, generating incorrect citations, and encouraging moral reflection on the effects of AI on society [37, 38]. Universities are now being forced to reevaluate conventional assessment methods and the changing role of artificial intelligence in academic settings, as educators increasingly use ChatGPT in their pedagogy to engage students critically with the technology. By connecting dispositional antecedents (personality) to cognitive assessments (trust) and behavioural outcomes (ChatGPT use), the proposed concept fills a significant research vacuum. According to the conceptualised framework, personality features affect the development of trust, which, in turn, influences behaviour and usage intention.

E. Hypothesis Development (The Big Five Personality Traits and Perceived Trust in the AI System)

Users' trust in ChatGPT and other AI systems is positively impacted by extraversion, defined as sociability and a desire for interpersonal connection [39]. According to de Winter *et al.* [16] and Kroczek *et al.* [40], extraverted people are more likely to interact with interactive agents, believe that they are socially responsive, and depend on their outputs. Extraversion is one personality trait shown to have a considerable impact on users' trust in AI [41]. Extraverts may be more likely to accept and embrace AI technology due to their communication skills and openness to contact [42]. These observations highlight the importance of user personality in promoting AI adoption and trust.

Increased interpersonal trust has been associated with agreeableness, characterised by qualities such as empathy, cooperation, and a preference for social harmony [43, 44]. People with high agreeableness are more inclined to approach human or artificial relationships with trust and openness [41]. Given their inclination towards constructive social interaction, these people might view ChatGPT and other AI systems as more reliable [45]. According to earlier research, agreeableness has a significant impact on users' trust in AI technology [42], highlighting the significance of personality-based characteristics in shaping adoption and trust.

Methodical and cautious decision-making is linked to conscientiousness, which is defined by diligence, dependability, and a strong sense of duty [46]. When it comes to AI, people with high conscientiousness are more inclined to trust programs like ChatGPT if they perceive the system as accurate, dependable, and consistent. Higher levels of trust are fostered when the technology satisfies their demand for structure and reliability. Conscientiousness has a major impact on trust in AI systems, according to research, which emphasises the need for AI designs that prioritise consistency and reliability to increase user acceptance.

Increased scepticism and caution are linked to neuroticism, which is characterised by emotional instability, anxiety, and a propensity towards negative affect [47]. Because they are more sensitive to danger and expect bad things to happen, people with high neuroticism may be more critical of AI systems like ChatGPT, thereby lowering perceived trust. Research indicates that neuroticism has a significant impact on people's trust in AI systems [48]. This emphasises the importance of creating AI systems that take into account the concerns of highly neurotic users to increase acceptance and trust.

A greater inclination to investigate new technologies is associated with openness, defined as creativity, intellectual curiosity, and a readiness to engage with new experiences [49]. Because of their curiosity and upbeat outlook on innovation, people with high openness are more likely to view AI systems like ChatGPT as reliable. Research indicates that openness has a significant effect on users' trust in AI. This means that, to increase acceptance and trust, AI systems should be designed to accommodate people's intellectual and exploratory inclinations [48]. Consequently, the following theories:

H1a: Extraversion significantly impacts users' perceived trust in AI technology, such that individuals with higher levels of extraversion are more likely to exhibit greater trust in its use and outputs.

H1b: Agreeableness significantly impacts users' perceived trust in AI technology, such that individuals with higher levels of agreeableness are more likely to demonstrate increased trust in its use and outputs.

H1c: Conscientiousness significantly impacts users' perceived trust in AI technology, such that individuals with higher levels of conscientiousness are more likely to exhibit cautious or measured trust in its use and outputs.

H1d: Neuroticism significantly impacts users' perceived trust in AI technology, such that individuals with higher levels of neuroticism are more likely to exhibit lower trust in its use and outputs due to increased anxiety, scepticism, or emotional sensitivity.

H1e: Openness significantly impacts users' perceived trust in AI technology, such that individuals with higher levels of openness are more likely to demonstrate increased trust in its use and outputs due to their greater receptiveness to new experiences and innovative technologies.

F. ChatGPT Perceived Trust and ChatGPT Use

One significant element influencing ChatGPT usage is trust [50]. According to a poll of 359 participants, consumer trust in the chatbot had a significant effect on their likelihood of continuing to use the service [51]. In a similar vein, a healthcare study found that trust is a crucial factor in determining whether people use chatbots to diagnose illnesses, with adoption significantly influenced by trust in conversational agents [52]. Trust is crucial for the acceptance and deployment of new digital solutions, as evidenced by numerous studies that demonstrate its beneficial effects on technology use [53]. Based on the above argument, we propose the following hypothesis:

H2: The self-reported ChatGPT usage behavior of

ChatGPT significantly increases with users' perceived trust in the AI technology, such that higher levels of trust are positively associated with greater frequency or extent of usage.

III. METHODS

A quantitative research methodology was utilised to evaluate the study hypotheses. Quantitative research method aims to provide an explicit interpretation of patterns, order, and designs among participants [54]. The proposed model includes the constructs of the Big Five personality traits, perceived trust, and ChatGPT use. The selection of the constructs used in this study, as conceptualised in the model (Fig. 1), was guided by the current body of scholarship.

This framework provides a psychologically grounded explanation of individual variability in AI adoption and contributes to ongoing efforts to understand user-AI interaction through both dispositional and technological lenses.

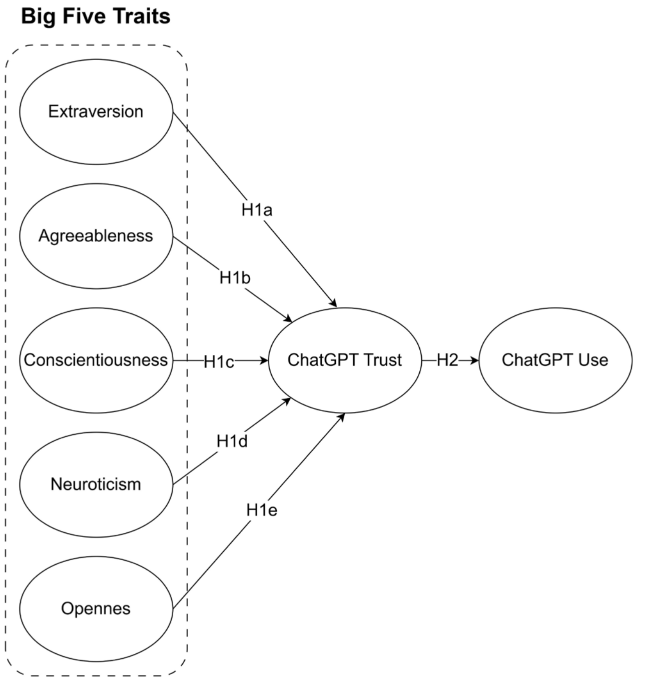

Fig. 1. Conceptual framework.

A. Sampling Technique and Sample Size

Purposive sampling, sometimes referred to as judgmental sampling, was employed to collect the required data using a structured questionnaire. Purposive sampling is a nonprobability sampling technique in which participants are chosen based on their knowledge and experience relevant to the research topic [55]. The authors used filter questions such as 'Do you use ChatGPT' to aid the participants' selection process. Given the drawbacks of random sampling, especially the potential for low response rates, judgmental sampling offers a more focused selection process, yielding a dataset that is both reliable and contextually relevant. Students from private universities in North Cyprus comprise the research population. A total of 370 surveys were sent, and 350 responses were received; 20 were discarded due to incomplete information. Abdelmoula *et al.* [56] confirmed that sample size has a positive effect on reliability. Additionally, several researchers have noted that sample size has an effect on reliability [57, 58]. Nunnally and Bernstein [59] claim that "measurement theory cannot usually tolerate large doses of sampling error..." and then recommend a sample size of "300 or more". Based on these studies, we safely confirm that this questionnaire is reliable, given the sample size of 330 participants.

B. Study Area

The population under investigation consists of university students in North Cyprus. North Cyprus is a pertinent and distinctive research locale owing to its swiftly growing higher education sector and diverse foreign student demographic [60]. North Cyprus accommodates an increasing number of universities that draw students from Africa, the Middle East, Asia, and Europe, fostering a cosmopolitan academic atmosphere [61]. In addition, the escalating digitalisation particularly following the COVID-19 pandemic, and the evolution of AI-related technologies have led to an increased use in academic environments such as North Cyprus. Thus, making the region a suitable environment for our study.

C. Data Collection Tool and Procedure

The authors developed and organised a questionnaire following a comprehensive review of relevant studies to ensure the reliability and validity of the survey instrument. Before collecting the data, a pilot study was conducted with 30 volunteers exhibiting an understanding of the research topic. The results demonstrated strong validity and reliability metrics, confirming that the research instrument is highly dependable and consistent, thus appropriate for the study (i.e., Cronbach's alpha > 0.70; AVE > 0.50). The inclusion criteria for this study included students aged 18 and above, students enrolled in higher education (universities), and those using Artificial Intelligence (ChatGPT). The study excluded individuals who did not meet the stated criteria. These criteria position the study to focus on a specific group likely to yield a significant contribution to the study's aim.

The questionnaire consists of two parts. The questionnaire was structured to include demographic information in the first part, including age, gender, and the participant's level of education. The second part consists of three variables with a distinct set of questions. The Big Five personality traits (extraversion, agreeableness, conscientiousness, neuroticism, and openness) with 10 items, perceived trust with 4 items, and ChatGPT use with 5 items were the constructs used in the study. The 10 items in the Big Five personality traits were adopted from [62]. Examples of the items include 'I see myself as someone who is reserved' and 'I see myself as someone who is generally trusting'. The 4 items of perceived trust were adopted by Shahzad *et al.* [63]. Examples of items include 'I believe using ChatGPT for interaction would be sufficiently secure' and 'I believe that ChatGPT will prevent anyone from accessing my personal information'. The 5 items for ChatGPT use were adopted from [64]. Examples of such items include 'I have used ChatGPT to assist with tasks, assignments, or other obligations and did not disclose its use' and 'Even if I trust ChatGPT's outputs, I feel uneasy about using it without acknowledging its use (reverse coded)'. Reverse coding is used in survey-based research to reduce response bias and enhance data quality. The authors used a

5-point Likert scale (1= strongly disagree to 5= strongly agree) to organise the questions. The authors also modified the items to fit the study's context.

Data collection lasted 2 months (17th March–15th May 2025). The authors distributed 370 questionnaires face-to-face. In total, 350 responses were received, 20 were invalid due to incomplete, missing values or erroneous entries. The final valid data used for analysis were 330, yielding an 89.2% response rate. Researchers typically require a minimum response rate of around 60% for survey results to be considered valid, although rates beyond 80% substantially bolster the credibility of the findings [65]. Therefore, the gathered data is reliable and credible in substantiating the research findings as posited in the model.

The sample comprised 330 participants, of whom 170 were female (51.5%). The majority of respondents were between 17 and 25 years of age (85.2%), and a substantial proportion were undergraduate students (88.8%). See Table 1.

Table 1. Demographic characteristics

Characteristic	Category	Frequency (N)	Percentage (%)
Gender	Male	160	48.5
	Female	170	51.5
Age	17–25	281	85.2
	26–30	41	12.4
	31–35	5	1.5
	36–40	3	0.9
Education	Undergraduate	293	88.8
	Postgraduate	37	11.2

D. Analysis

The analysis was performed using IBM SPSS version 26 for data cleaning and SmartPLS 4 to validate the measurement model and to assess the Structural Equation Modelling (SEM). SEM was chosen in this study for its capacity to examine complex, multi-variable relationships between latent constructs such as personality traits, perceived trust and ChatGPT use, while simultaneously controlling for measurement error [66]. SEM ensures statistical precision in confirming the proposed conceptual framework by providing robust model fit indices and enabling the simultaneous assessment of multiple dependent and independent variables, in contrast to simpler analytical techniques. For the path analysis, the authors employed SmartPLS 4. SmartPLS is a software for model testing [66]. The software makes it possible to specify indicators for the indicator and build a path model between them. One advantage of this path modelling technique is that it does not require distributional assumptions and can accommodate smaller sample sizes. Variables in SmartPLS may be interval scaled, like the Likert scale, nominal, or ordinal.

IV. Results

A. Measurement Model (Convergent Validity)

Measurement model fit indices, Cronbach's alpha reliability, composite reliability, standardised factor loadings, average variance extracted, and variance inflation factor were all used to assess convergent validity [67]. Table 2's findings show that all standardised factor loadings were higher than the suggested cutoff of 0.70, indicating that the minimal conditions for convergent validity were met [68]. Additionally, Cronbach's alpha values were deemed acceptable, remaining higher than 0.70 [69], while composite reliabilities were at or below 0.80. All constructs exhibited average variance retrieved exceeding 0.5 as shown. The variance inflation factor results demonstrate the absence of multicollinearity, as all values remained below the threshold of 3.3 [70].

Table 2. Reliability and validity

Construct	Loadings	α	CR	AVE	VIF
EXT1	0.931	0.736	0.880	0.785	1.513
EXT2	0.840				1.513
AGR3	0.819	0.625	0.841	0.726	1.261
AGR4	0.884				1.261
CON5	0.875	0.833	0.917	0.847	2.036
CON6	0.963				2.036
NEU7	0.915	0.758	0.891	0.804	1.595
NEU8	0.878				1.595
OPEN9	0.885	0.805	0.909	0.834	1.832
OPEN10	0.941				1.832
CHU1	0.735	0.825	0.877	0.589	1.510
CHU2	0.837				1.979
CHU3	0.777				1.717
CHU4	0.744				1.645
CHU5	0.738				1.615
PTR1	0.802	0.793	0.865	0.617	1.724
PTR2	0.858				2.045
PTR3	0.727				1.528
PTR4	0.748				1.576

Note: α: alpha; CR: composite reliably; AVE: average variance extracted; AGR: agreeableness; CON: consciousness; EXT: extraversion; NEU: neuroticism; OPEN: openness; PTR: ChatGPT perceived trust; CHU: ChatGPT Usage.

B. Discriminant Validity

Table 3. Fornell and Larcker criterion and HTMT

Method	Construct	AGR	CHU	CON	EXT	NEU	OPEN	PTR
Fornell and Larcker Criterion	AGR	**0.852**						
	CHU	0.185	**0.767**					
	CON	0.142	0.182	**0.920**				
	EXT	0.190	0.085	0.254	**0.886**			
	NEU	−0.106	−0.164	−0.063	−0.176	**0.897**		
	OPEN	0.265	0.315	0.215	0.076	−0.136	**0.913**	
Heterotrait - monotrait ratio (HTMT)	AGR							
	CHU	0.246						
	CON	0.181	0.207					
	EXT	0.288	0.124	0.337				
	NEU	0.161	0.195	0.068	0.228			
	OPEN	0.352	0.365	0.242	0.097	0.167		
	PTR	0.332	0.719	0.230	0.224	0.350	0.435	

Discriminant validity is presented in Table 3. The results show that each factor was significantly correlated with the other. The square roots of the AVE values (reported in the off-diagonal, Table 3), which measure the Fornell and

Larcker Criterion, were higher than the cross-correlations [71]. To attain validity using HTMT indicator, the ratio must fall below or equal 0.90. Since the cut-off points were met, we safely confirm that discriminant validity is established [72].

C. Testing Research Hypotheses—(Structural Equation Modelling)

The hypotheses proposed in this study were empirically tested, and the results are presented in Table 4. H1a examined the influence of Extraversion (EXT) on Perceived Trust (PTR) and yielded a non-significant effect (β = 0.078, t = 1.447, p > 0.05), hence H1a was rejected. H1b tested the impact of Agreeableness (AGR) on PTR and was supported, as the relationship was statistically significant (β = 0.110, t = 2.062, p < 0.05). H1c evaluated the effect of Conscientiousness (CON) on PTR and was rejected due to a non-significant result (β = 0.089, t = 1.797, p > 0.05). Neuroticism (NEU) and PTR were evaluated in H1d, and the results showed a significant negative influence (β = −0.204, t = 3.747, p < 0.05), supporting H1d. H1e investigated how openness to experience (OPEN) affected PTR; the results were significant (β = 0.278, t = 4.993, p < 0.05), supporting H1e. Lastly, H2 examined if PTR had a substantial impact on ChatGPT Use (CHU). The findings supported H6 with a strong, statistically significant connection (β = 0.597, t = 15.039, p < 0.05). The structural model was assessed through path coefficients, which were used to determine the significance and strength of the hypothesized relationships. Bootstrapping is used to repetitively estimate the path model using slightly varied data configurations. After bootstrapping, Fig. 2 displays the link between the variables under investigation.

Table 4. Path coefficient

Hypothesis	Path	β	Mean	Standard deviation	*T* statistics	*P* values	Bias	2.5%	97.5%	Decision
H1a	EXT→PTR	0.078	0.083	0.054	1.447	0.148	0.005	−0.030	0.175	Rejected
H1b	AGR→PTR	0.110	0.112	0.053	2.062	0.039	0.002	0.005	0.214	Supported
H1c	CON→PTR	0.089	0.090	0.050	1.797	0.072	0.001	−0.007	0.184	Rejected
H1d	NEU→PTR	−0.204	−0.210	0.055	3.747	0.000	−0.005	−0.307	−0.093	Supported
H1e	OPEN→PTR	0.281	0.278	0.056	4.993	0.000	−0.003	0.169	0.388	Supported
H2	PTR→CHU	0.597	0.601	0.040	15.039	0.000	0.004	0.507	0.668	Supported

H1: ChatGPT Trust (R2= 0.215; Q²predict= 0.177);
H2: ChatGPT Use (R2=356; Q²predict= 0.107).

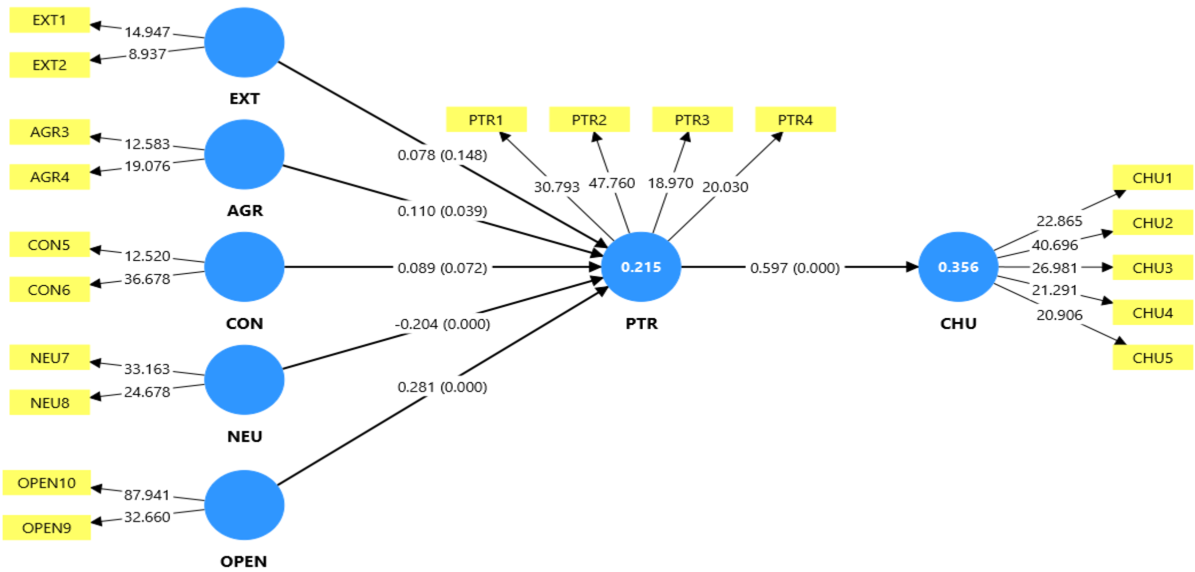

Fig. 2. Structural model indicating t-statistics (After bootstrapping).

V. Discussion

The results of this study provide important insights into the psychological factors driving trust in AI. Two concepts that elucidate the relationships between the constructs are synthesised in this article. Thus, relating cognitive evaluations (trust) and behavioural outcomes (ChatGPT use) to dispositional antecedents (personality).

It was found that extraversion (H1a) had no significant impact on ChatGPT perceived trust. This finding contrasts with the previous research demonstrating a positive relationship between extraversion and trust in interactive or social systems [16, 42]. Although extraverted people accept social interaction, they might not consider conversational AI sufficiently “social” to elicit trust-related behaviours, which could explain this lack of relevance. The importance of extraversion in this context may be limited by the lack of human reciprocity or emotional complexity in AI interactions.

Consistent with the existing literature, agreeableness (H1b) demonstrated a significant positive connection with perceived trust [44]. Because they are naturally cooperative and trustworthy, agreeable consumers may be more likely to see AI technologies as reliable and advantageous. Their propensity for social cohesiveness and empathy probably enhances their use of AI-mediated communication tools.

Contrary to previous research [73] that showed conscientious people value the dependability and organised qualities provided by efficient AI systems like ChatGPT, the connection between conscientiousness and perceived trust

(H1c) was not significant. The results of this study indicate that, until they can consistently assess the AI's correctness and reliability over time, conscientious people are likely to be more sceptical or critical. Their cautious approach to decision-making could make it more difficult to build trust, particularly with new or unfamiliar technologies.

In line with earlier studies, a significant inverse relationship between neuroticism and perceived trust (H1d) was found [14]. Because neurotic people are prone to worry, scepticism, and emotional instability, they are more vulnerable to perceived risks or uncertainties associated with AI technologies. Even minor errors or ambiguities in AI responses can seriously undermine trust and lead to scepticism or avoidance.

Openness (H1e) confirmed [74] findings by showing a strong positive effect on perceived trust. Open people tend to be inventive, inquisitive, and open to new concepts qualities that naturally align with the study of emerging technologies like ChatGPT. inevitably, their enthusiasm for innovation raises trust levels, especially in systems that are seen as innovative or thought-provoking.

Perceived trust was found to have a major and significant impact on ChatGPT usage (H2), supporting earlier studies that found trust to be a critical component of AI adoption and usage behaviour [75]. Users are more likely to integrate technology into their tasks and daily routines when they believe it is dependable, underscoring the need to build trust through dependable performance and user-friendly design.

The findings demonstrate that individual differences greatly influence users' attitudes and actions towards AI, and that not all personality traits have an equal impact on trust. The presence of insignificant or negative impacts underscores the complexity of human-AI interaction and the importance of adapting AI systems to diverse psychological profiles.

VI. Conclusion

This study investigated the influence of personality traits on self-reported use of ChatGPT and the mediating role of trust in this relationship, drawing on the Big Five personality traits and situating the analysis within the broader technology adoption literature. The results indicate that agreeableness, openness, and neuroticism significantly influence perceived trust, whereas extraversion and conscientiousness do not. Furthermore, trust demonstrates a strong effect on ChatGPT usage behavior, underscoring its central role in users' engagement with AI technologies. These findings enhance understanding of the psychological factors shaping trust in and use of generative AI systems and provide valuable insights for the responsible design, development, and deployment of AI applications in educational and related settings.

In terms of practice, the study's findings have implications for UX designers, educators, and AI developers. Building AI systems that foster trust across a range of personality types is crucial, as trust is a powerful predictor of ChatGPT usage. Emphasising openness, creativity, and adventurous qualities can increase engagement among friendly, responsive people. Interfaces designed for users with high levels of neuroticism should prioritise emotional stability, accuracy, and openness in handling errors.

Educational Institutions should assess how individual differences impact students' trust and the efficient use of AI tools. Students' confidence and critical participation can be increased by integrating AI literacy into curricula that discuss both its benefits and limitations. Ethical AI integration in education can be improved by developing learning environments that support open-minded learners' inquiry while offering reassurance and structured direction to cautious or neurotic learners.

From a management perspective, the results highlight the importance of user diversity in AI adoption campaigns, encompassing both corporate and academic management. In academic and professional settings, people with different personality types will react differently to AI systems. Managers and institutional leaders should provide specialist training and support that addresses trust barriers, particularly for users who might show increased concern or scepticism. For academic environments to foster trust and widespread adoption, it will be crucial to encourage open communication, provide feedback channels, and clarify ethical guidelines for AI use.

While the findings contribute to understanding AI adoption in educational contexts, several limitations should be acknowledged. First, the study relies on a cross-sectional design and self-reported usage behavior, which may not fully capture actual system use. Secondly, using only two items to measure each Big Five personality dimension may limit reliability and content validity.

Future research could employ longitudinal designs to examine how trust in AI evolves with increased experience, training, or institutional exposure. Given the strong relationship observed between trust and self-reported usage behavior, future studies are encouraged to refine measurement approaches by distinguishing attitudinal perceptions from behavioral indicators of use. Additionally, extending this research to diverse educational contexts and stakeholder groups, such as academic staff and instructors and integrating factors such as perceived academic risk, digital self-efficacy, and learning autonomy, may further enhance understanding of responsible and effective AI deployment in education.

Conflict of Interest

The author declares no conflict of interest.

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