The Influence of Extraversion and Neuroticism on Technology Acceptance and Cognitive Dissonance in LLM Usage

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***Abstract*—In our cross-sectional study, we examine how personality traits influence students' acceptance of Large Language Models (LLMs) in higher education. Building on the Technology Acceptance Model, the Big Five framework, and Cognitive Dissonance Theory, we focus on Extraversion and Neuroticism as predictors of LLM Usage. We conducted an online survey with 120 psychology students, measuring personality traits, Technology Acceptance, LLM Usage, and Cognitive Dissonance. Extraversion showed no significant association with either acceptance or dissonance. Neuroticism had a negative direct effect on Technology Acceptance, and we observed a small positive indirect effect via Cognitive Dissonance that warrants cautious interpretation. These results may help explain why some more neurotic students nonetheless accept LLMs.**

Keywords-technology acceptance; cognitive dissonance; personality traits; extraversion; neuroticism; human–computer interaction.

I. Introduction

Large Language Models (LLMs), such as ChatGPT, Gemini, or Perplexity AI have rapidly entered higher education, transforming how people access, generate, and interact with information [1]–[3]. Universities increasingly integrate these tools to support teaching and learning (e.g., [4]–[6]). At the same time, limited transparency and reliability raise concerns about trust, critical evaluation, and responsible use [7]. These tensions raise a central question for both educational practice and research in Human-Computer Interaction (HCI): When and why do students adopt LLMs, and how do personality traits influence this adoption?

Technology Acceptance Models provide well-established frameworks for explaining adoption, emphasizing perceived usefulness, ease of use, and user experience as key predictors [8][9]. However, these models often treat users as homogeneous and overlook how individual differences shape acceptance. Students bring diverse expectations, practices, and psychological traits that influence how they interact with AI technologies.

Prior work shows that personality traits—especially Extraversion and Neuroticism—are associated with trust and technology use, with Extraversion linked to higher acceptance and Neuroticism to skepticism or lower usability perceptions [10]–[12]. [13] found that higher neuroticism and extraversion were associated with a more serious perceived AI-related threat. However, empirical research on personality in the context of LLM use is scarce [14]. The role of Cognitive Dissonance—the discomfort when expectations diverge from experience [15]—also remains underexplored, even though the error-prone and sometimes contradictory nature of LLMs may elicit dissonance that shapes acceptance and continued use. Therefore, understanding how students adopt LLMs requires an interdisciplinary perspective that integrates educational technology, personality psychology, and human–computer interaction. Prior research highlights both the transformative potential of AI in higher education [1][5][16] and challenges around transparency, trust, and responsible use [17][18], underscoring the relevance of personality-driven differences in learners' engagement with LLM-based tools.

In our study, we address these gaps by examining how Extraversion and Neuroticism relate to students' acceptance of LLMs and their experience of Cognitive Dissonance. Drawing on the Technology Acceptance Model [8], the Big Five personality framework [19], and Cognitive Dissonance Theory [15], we model Cognitive Dissonance as a mediator between personality and LLM acceptance and quantify its contribution to the Technology Acceptance of LLMs.

Our study offers three contributions:

1) **Empirical**: we provide quantitative evidence on the role of personality and Cognitive Dissonance in LLM adoption;
2) **Theoretical**: we extend acceptance models with psychological factors to better explain diverse user experiences;
3) **Practical**: we derive implications for designing adaptive, human-centered AI tools that support trust, equity, and well-being in higher education.

The remainder of this paper is structured as follows. In Section 2, we review the theoretical background on AI in education, personality psychology, technology acceptance models, and cognitive dissonance. In Section 3, we present the study design, including research questions, hypotheses, sample characteristics, instruments, and analytical procedures. In Section 4, we report the empirical results of the correlation and mediation analyses. In Section 5, we discuss the findings in relation to existing literature, outline implications for human–computer interaction and educational practice, and address limitations. Finally, in Section 6, we conclude with a summary of key insights and directions for future research.

II. Background

To frame our study, this section reviews three key areas: the integration of AI and LLMs in education (Section II-A), personality psychology with a focus on the personality traits Extraversion and Neuroticism (Section II-B), and established technology acceptance models and their extensions (Section II-C). Moreover, we address Cognitive Dissonance Theory to explain how discrepancies between expectations and experiences may influence user acceptance in Section II-D.

A. AI in Education

Recent LLMs, such as ChatGPT, Gemini, and Perplexity AI, enable human-like interaction and have been rapidly integrated into both everyday life and academic contexts [2][3], making them powerful tools for education and research. However, concerns remain regarding reliability, transparency, and critical evaluation of generated content [7]. The use of LLMs in higher education is a relatively new and emerging field. Students frequently use text-generating AI tools, such as ChatGPT, primarily because of their ease of access rather than systematic pedagogical integration [7]. Current studies suggest that acceptance of these technologies can be explained through established models of technology adoption, such as the Technology Acceptance Model (TAM) [7], which emphasize user perceptions that significantly shape adoption decisions [20].

B. Personality Psychology and the Big Five Model

Personality refers to systematic interindividual differences in cognition, affect, and behavior [21]. One of the most established frameworks in personality psychology is the Big Five model (OCEAN) [19], which conceptualizes personality along five continuous dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [22].

At the intersection of psychology and HCI, personality traits have been increasingly studied as predictors of Technology Acceptance. In our study, we focus on Extraversion and Neuroticism, which are strongly linked to trust, attitudes, and acceptance of AI technologies [10]. Extraversion has been linked to higher acceptance of digital tools and positive evaluations of social technologies [11][23], whereas Neuroticism relates to lower perceived usefulness, reduced trust, and higher uncertainty and skepticism, potentially reducing acceptance [10][24]. From the perspective of Cognitive Dissonance Theory, individuals high in Neuroticism are more prone to negative affect and thus more likely to experience dissonance when system outputs conflict with expectations. In contrast, extraverted individuals typically show more positive affect and resilience in coping with such discrepancies [15][25].

C. Technology Acceptance Models in the Context of LLMs

The TAM, originally proposed by Davis [8], provides a framework for understanding why individuals adopt or reject specific technologies. It highlights two central constructs: *Perceived Usefulness* (the belief that using a technology enhances performance) and *Perceived Ease of Use* (the degree to which a technology is considered effortless to use), which shape user attitudes, behavioral intentions, and actual system usage. Perceived usefulness is generally the strongest direct predictor of Technology Acceptance, while perceived ease of use additionally influences perceived usefulness [8].

TAM has been extended to account for external factors. TAM2 [9] adds social influences (e.g., subjective norms, image) and cognitive processes (e.g., job relevance, output quality, voluntariness) to improve predictive validity. Unified Theory of Acceptance and Use of Technology (UTAUT) [26] integrates multiple frameworks into a comprehensive model. The Media and Technology Usage and Attitudes Scale (MTUAS) [27] broadens the focus by incorporating psychological aspects of everyday technology use, including trust, compatibility, and satisfaction. In parallel, the Digital Technology Acceptance Scale (DTAS) [28], developed as an extension of TAM [9][26], is used to study AI-based systems like LLMs.

While TAM and its extensions have been validated across various technologies, their application to AI-based systems, particularly LLMs, raises new questions. Classical constructs, such as perceived usefulness and perceived ease of use, remain relevant, but additional factors come into play: transparency, trust, and ethical considerations are central to AI acceptance [7], and the black-box nature of LLMs can undermine trust, as users may struggle to evaluate the reliability of outputs. Studies indicate that social influences and prior experience shape acceptance of generative AI in higher education [20]. Students often adopt LLMs for pragmatic reasons such as efficiency and accessibility. Yet, their long-term integration depends on whether the tools are perceived as credible and aligned with academic values. Furthermore, acceptance is influenced by personality traits (e.g., Extraversion, Neuroticism) and cognitive processes (e.g., dissonance when outputs conflict with expectations), which are not fully captured by classical TAM variables. Therefore, in educational settings, extended models, such as DTAS, are especially relevant, as they incorporate behavioral intention and enjoyment. This is critical for understanding whether students use LLMs, why they integrate them into their study practices, and how they experience them, since preferences may vary across different learner profiles [28].

D. Cognitive Dissonance in LLM Usage

Cognitive Dissonance Theory [15] describes the psychological discomfort that arises when individuals hold conflicting cognitions (e.g., expectations vs. actual experiences), motivating efforts to restore consistency by changing attitudes, behaviors, or avoiding dissonant situations.

Applied to LLM Usage, this framework highlights new challenges when performance expectations are not met: the inconsistency between expectations and outcomes can trigger negative emotions [25]. In the context of students using LLMs, dissonance may arise when expectations about reliability or accuracy do not align with received outputs [29]. Since LLMs are prone to generating errors or false information, confronting misinformation can provoke dissonance [30], especially when students rely heavily on the correctness of generated content but later realize limitations, undermining both trust in the system and self-confidence. Evaluating and correcting such misinformation is central for individual well-being and broader reliability of technology in educational settings [31]. Festinger's principles thus provide a powerful lens on emotional and cognitive reactions in interaction with LLMs, especially in education, where unresolved dissonance can shape learning behaviors, attitudes toward technology, and long-term patterns of adoption or avoidance.

III. Study Overview and Design

In our study, we aim to find out how personality traits and Cognitive Dissonance influence the Technology Acceptance of psychology students. After presenting our research questions, we describe the research methodology we applied in our study.

A. *Research Questions and Hypotheses*

The theoretical background on Technology Acceptance and Cognitive Dissonance suggests that personality traits may shape how students perceive and adopt LLMs. While prior work emphasizes the central role of perceived usefulness and ease of use [8][9], there is limited empirical evidence on how personality-driven factors, such as Extraversion and Neuroticism, influence acceptance in educational AI contexts. Moreover, Cognitive Dissonance may act as an additional explanatory mechanism when expectations and experiences with LLMs diverge [15][25].

Based on the theoretical framework outlined above, Table I summarizes the research questions and corresponding hypotheses examined in this study.

TABLE I. Research questions and hypotheses.

ID	Description
RQ1	How does Extraversion relate to students' acceptance of LLMs?
RQ2	How does Neuroticism relate to Cognitive Dissonance when interacting with LLMs?
RQ3	Does Cognitive Dissonance mediate the relationship between Neuroticism and Technology Acceptance?
RQ4	How do personality traits relate to actual LLM Usage?
H1	Extraversion is positively associated with Technology Acceptance of LLMs.
H2	Neuroticism is positively associated with Cognitive Dissonance when using LLMs.
H3a	Cognitive Dissonance negatively mediates the relationship between Neuroticism and Technology Acceptance.
H3b	(exploratory) Technology Acceptance positively mediates the relationship between Extraversion and LLM Usage.
H4	(exploratory): Neuroticism is negatively associated with Technology Acceptance of LLMs.
H5	(exploratory): Extraversion is negatively associated with Cognitive Dissonance when using LLMs.

Figure 1 presents the direct hypotheses, while Figure 2 shows the mediation hypotheses, integrating personality traits, Technology Acceptance, and Cognitive Dissonance.

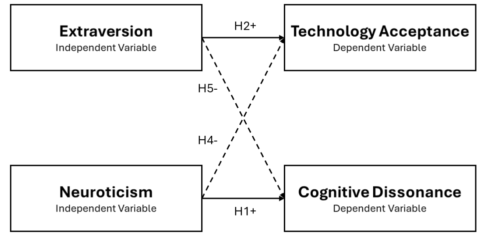

Figure 1. Direct hypotheses. Dashed arrows indicate exploratory hypotheses.

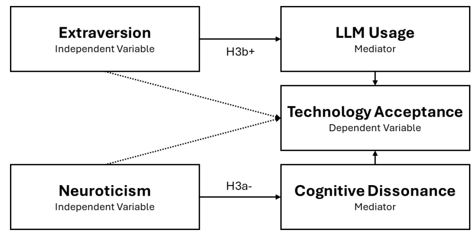

Figure 2. Mediation hypotheses. Solid arrows represent indirect paths, dotted arrows represent direct paths.

B. *Data Collection and Participants*

Data were collected between May and June 2025 using an online questionnaire. We recruited 127 participants, mostly students from IU International University of Applied Sciences but also from psychology-related social media channels, such as WhatsApp groups. Before participation, all students were informed about the purpose of the study and data protection regulations in accordance with the GDPR, and they provided informed consent. Participants without a background in psychology and those younger than 18 years were excluded.

We focused on psychology students as they form a particularly relevant population for examining the relationship between personality traits and LLM Usage. Personality constructs, such as the Big Five model, are central to their field of study, which enhances familiarity with self-report instruments and therefore increases data quality. Moreover, psychology students frequently engage in text-based academic tasks (e.g., essays, literature reviews) and are therefore likely to experiment with tools like ChatGPT. Using a relatively homogeneous sample also reduces potential confounding effects of disciplinary differences and allows a clearer examination of personality-driven influences.

We used a quantitative, correlational design with a cross-sectional online survey, where participants rated items on Likert-type scales. Experimental manipulation was not used, as personality traits cannot be manipulated in this context. Therefore, a correlational design was adopted to examine the relationships between personality traits, Technology Acceptance, Cognitive Dissonance, and LLM Usage. An a-priori power analysis indicated a minimum sample size of $N = 84$ to test **H1** and **H2** (medium effects: $\rho = .30$, $\alpha = .05$, $1 - \beta = .80$). For the mediation hypotheses **H3a** and **H3b**, assuming a small-to-medium effect size ($f^2 = 0.06$), a minimum sample size of $N = 120$ was required to achieve adequate power ($\alpha = .05$, $1 - \beta = .80$). Since all hypotheses were tested within the same study, a total sample size of $N = 120$ participants was necessary.

C. *Data Preparation and Cleaning*

All items were measured on Likert-type or frequency scales. For each construct, we computed mean scores across the respective items and treated these composite scores as approximately interval-scaled. We inspected missing values and removed cases with excessive missing data listwise; scale

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scores were computed, handling remaining missing responses on single items if at least half of the items for a given construct were available. Internal consistencies (Cronbach's α) were calculated to ensure reliability of the aggregated scales.

To ensure data quality, we embedded two attention checks in the questionnaire and included only participants who answered both correctly. In addition, we applied a lower time threshold of two minutes. Cases with substantially shorter times were checked for plausibility and excluded if necessary.

The Usage Frequency Scale [27], originally with ten response categories, was reduced to nine categories in the present study to ensure compatibility with the other scales.

D. Sample Characteristics

After data preparation and cleaning, the final sample included $N = 120$ valid cases for analysis. Table II summarizes the demographic data of the study participants. Participants were between 18 and 45 years old, with a mean age of 24.91 years (SD = 5.48).

TABLE II. SOCIODEMOGRAPHIC DATA OF THE FINAL SAMPLE ($n = 120$).

Characteristic	Category	Sample n	Percent
Gender	Male	7	5.83%
	Female	112	93.33%
	Diverse	1	0.83%
Degree	Bachelor	116	96.67%
	Master	3	2.50%
	Postgraduate	1	0.83%

Figure 3 summarizes which AI technologies are used by the study participants. The most frequently used type of AI technology was text-generating AI chatbots, followed by voice assistants like Siri or Alexa.

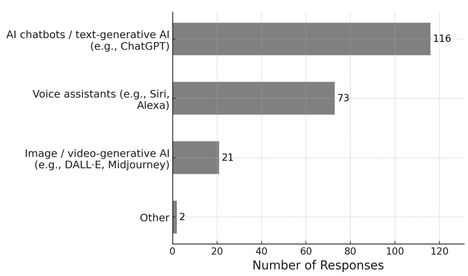

Figure 3. Types of AI technologies used (multiple answers allowed).

Figure 4 shows that study participants employed LLMs most frequently in academic contexts.

E. Instruments

We used validated questionnaires to measure the key constructs underlying our research questions. All Likert scales used 1-5 response options unless otherwise noted.

1) Personality: To assess Extraversion and Neuroticism, we used the Big Five Inventory (BFI-44) [32], each trait captured with 8 items on a 5-point Likert scale. As we did not use the full questionnaire, we conducted a reliability analysis. The original Extraversion subscale showed insufficient reliability

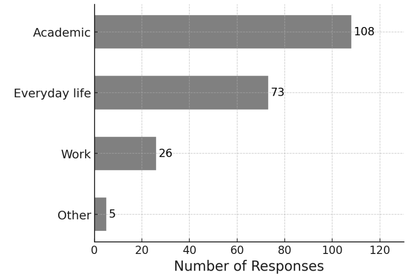

Figure 4. Context of LLM Usage (multiple answers allowed).

(Cronbach's $\alpha = .353$). Two items with negative item–total correlations were removed, resulting in a 6-item Extraversion scale. The Neuroticism subscale already demonstrated satisfactory internal consistency, so no items were excluded. For the final sample, internal consistencies were $\alpha = .849$ for Extraversion and $\alpha = .860$ for Neuroticism, indicating good reliability.

2) LLM Usage: To assess LLM Usage, we developed a new subscale based on MTUAS [27]. We reduced the original ten-point frequency scale to nine options due to redundancy in the highest categories. Items covered typical application contexts, such as information search, creative writing, academic text editing, study support, and rapid problem-solving [33][34]. The subscale showed high internal consistency ($\alpha = .890$). An exploratory factor analysis confirmed a one-factor structure ($KMO = .844$; Bartlett's test $\chi^2(10) = 363.49$, $p < .001$).

3) Technology Acceptance: Technology Acceptance was measured with a 13-item scale adapted from the DTAS [28], a validated German instrument based on the classical TAM framework. Items were randomized to avoid response patterns and answered on a five-point Likert scale. The scale demonstrated excellent internal consistency in the present sample ($\alpha = .925$).

4) Cognitive Dissonance: To the best of our knowledge, no established instrument exists to measure Cognitive Dissonance in the context of LLMs. We therefore adapted the well-established scale by Sweeney et al. [35], originally developed for purchase decisions, which can be contextually adapted to LLM Usage without loss of content structure. The 22 items cover three dimensions: emotions, wisdom of purchase, and concern over deal. Therefore, we calculated an overall average for all items. To preserve this thematic grouping, items were presented in thematic blocks rather than fully randomized. We provided an instructional text with a concrete example to enhance response quality. All items were rated on a five-point Likert scale. The adapted scale showed high internal consistency in our sample (Cronbach's $\alpha = .894$).

F. Assumption Testing

To test **H1** and **H2**, we conducted correlation analyses between Extraversion or Neuroticism and Technology Acceptance or Cognitive Dissonance. Normality, assessed with Shapiro–Wilk tests, was not met. Given the ordinal scaling of the variables and the sample size, Spearman's correlation was used.

For **H3a**, we tested a mediation model with Neuroticism (independent variable), Cognitive Dissonance (mediator), and Technology Acceptance (dependent variable) following [36]. Because the mediator and dependent variables deviated from normality in Shapiro–Wilk tests, we used bootstrap mediation with 5,000 samples and 95% CIs, which does not assume normality and provides robust estimates. Effects were considered significant if the interval did not include zero. As Extraversion was unrelated to technology acceptance and LLM usage, **H3b** was treated as exploratory.

The exploratory hypotheses **H4** and **H5** were tested analogously to **H1** and **H2** using Spearman's rank correlations, as assumptions for parametric tests were not met.

IV. Results

To evaluate our hypotheses, we first present the descriptive statistics of the central variables in Table III. Extraversion and Neuroticism are centered around the scale midpoints with moderate variance. Technology Acceptance ratings were generally positive, while Cognitive Dissonance was reported at moderate levels. LLM Usage varied considerably, with most participants reporting occasional use, but a small subgroup indicating high-frequency engagement.

TABLE III. Descriptive statistics of main variables.

Variable	Mean (SD)	Range
Extraversion	3.21 (0.74)	1–5
Neuroticism	2.99 (0.73)	1–5
Technology Acceptance	3.63 (0.73)	1–5
Cognitive Dissonance	2.11 (0.67)	1–5
LLM Usage	4.05 (1.94)	1–9

A. *Extraversion and Technology Acceptance (**H1**)*

Contrary to our expectations, Extraversion did not predict higher acceptance of LLMs. The correlation between Extraversion and Technology Acceptance was very weak and non-significant ($r_s = .061$, $p = .509$). Thus, **H1** could not be confirmed. As shown in Figure 5, no systematic patterns emerge.

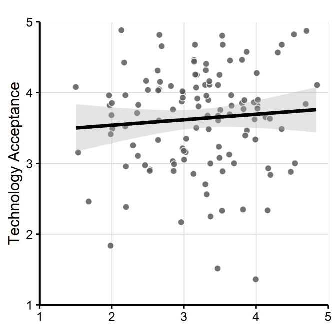

Figure 5. Correlation of Extraversion and Technology Acceptance.

These findings suggest that sociability and outgoingness do not substantially influence whether students perceive LLMs as useful or easy to use.

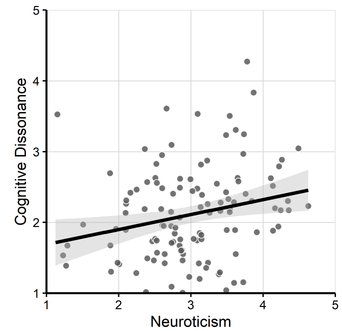

Figure 6. Correlation of Cognitive Dissonance and Neuroticism.

B. *Neuroticism and Cognitive Dissonance (**H2**)*

The analysis revealed a small-to-moderate, statistically significant positive association between Neuroticism and Cognitive Dissonance in the expected direction ($r_s = .243$, $p = .008$). Thus, the results provide statistical evidence for a relationship between Neuroticism and the experience of Cognitive Dissonance when using LLMs in the present sample.

Figure 6 illustrates the positive association between Neuroticism and Cognitive Dissonance.

C. *Mediation of Cognitive Dissonance between Neuroticism and Technology Acceptance (**H3a**)*

Neuroticism significantly predicted Cognitive Dissonance (estimate $= 0.315$, $SE = 0.121$, $p = .009$, 95%-CI [0.057; 0.558]) and Cognitive Dissonance positively predicted Technology Acceptance (estimate $= 0.225$, $SE = 0.090$, $p = .013$, 95%-CI [0.023; 0.448]). Bootstrapping indicated a small indirect effect (estimate $= 0.071$, $SE = 0.039$, 95%-CI [0.005; 0.212]) that was significant by our CI criterion (95%-CI excluded 0), although the associated p-value was slightly above $.05$ ($p = .072$). The direct effect of Neuroticism on Technology Acceptance remained negative and significant (estimate $= -0.293$, $SE = 0.121$, $p = .017$, 95%-CI [–0.505; –0.047]), indicating a partial mediation. These results suggest that Cognitive Dissonance partly mediates the relationship between Neuroticism and Technology Acceptance of LLMs.

Figure 7 provides an overview of the mediation model linking Neuroticism, Cognitive Dissonance, and Technology Acceptance of LLMs.

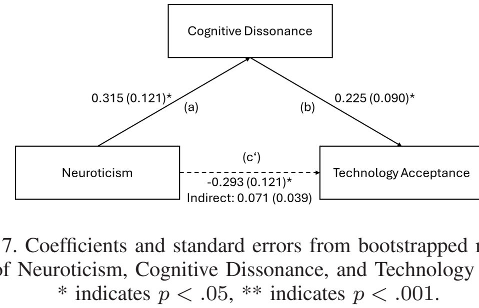

Figure 7. Coefficients and standard errors from bootstrapped mediation analysis of Neuroticism, Cognitive Dissonance, and Technology Acceptance. * indicates $p < .05$, ** indicates $p < .001$.

D. Mediation of Technology Acceptance between Extraversion and LLM Usage (*H3b*)

Extraversion neither predicted LLM Usage (estimate = 0.016, $SE = 0.095$, $p = .869$, 95%-CI [–0.158; 0.174]) nor Technology Acceptance (estimate = 0.106, $SE = 0.123$, $p = .388$, 95%-CI [–0.149; 0.353]), whereas Technology Acceptance strongly predicted LLM Usage (estimate = 0.642, $SE = 0.070$, $p < .001$, 95%-CI [0.530; 0.758]). The indirect effect of Extraversion via Technology Acceptance was non-significant (estimate = 0.068, $SE = 0.079$, $p = .390$, 95%-CI [–0.100; 0.226]).

Figure 8 illustrates the mediation model that links Extraversion, Technology Acceptance, and LLM Usage.

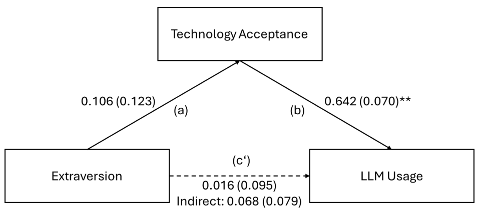

Figure 8. Coefficients and standard errors from bootstrapped mediation analysis of Extraversion, Technology Acceptance, and LLM Usage. * indicates $p < .05$, ** indicates $p < .001$.

E. Neuroticism and Technology Acceptance (*H4*)

Spearman's correlation indicated a weak, non-significant negative association between Neuroticism and Technology Acceptance ($r_s = -.157$). The significance level ($p = .087$) was slightly above the threshold of 0.05. This suggests only a small trend that might reach significance in larger samples, with Neuroticism explaining little variance in Acceptance. Figure 9 visualizes this weak negative trend.

The regression line indicates a small negative relationship.

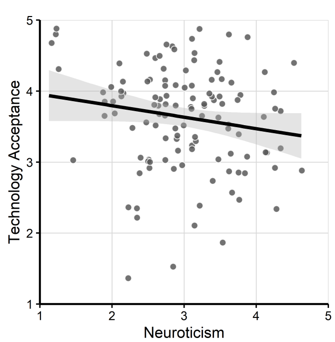

Figure 9. Correlation of Neuroticism and Technology Acceptance.

F. Extraversion and Cognitive Dissonance (*H5*)

Extraversion showed a weak, non-significant negative correlation with Cognitive Dissonance ($r_s = -.136$, $p = .138$), indicating no meaningful association, which is also reflected in Figure 10. The effect size ($z = -.137$) was smaller than the associated standard error ($SE = 0.093$), which further indicated low stability of the effect.

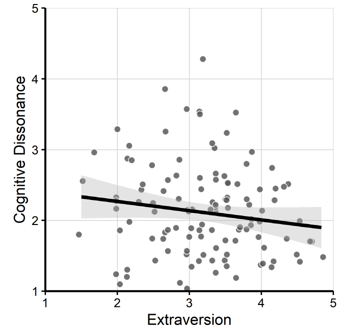

Figure 10. Correlation of Extraversion and Cognitive Dissonance.

V. Discussion

Our results provide first indications that are relevant for both theory and design. The unexpected mediation might suggest a mechanism-level explanation in which Cognitive Dissonance helps understand why neuroticism could be related to higher LLM acceptance. In contrast, the non-significant result for **H1** could indicate a possible boundary condition for extraversion in this context.

A. Interpretation of Main Findings

H1 was not supported: Extraversion was not related to Technology Acceptance of LLMs. This contrasts with prior work that found Extraversion to be a key predictor of Technology Acceptance [23][37] and may partly reflect our specific sample of psychology students.

H2 revealed a positive correlation between Neuroticism and the experience of Cognitive Dissonance when using LLMs. This confirms our hypothesis, even though the effect size was small. The findings suggest that psychology students with higher levels of Neuroticism tend to experience stronger Cognitive Dissonance when interacting with LLMs. They report more intense negative emotions when disappointed by the technology [25]. Because Neuroticism leads to heightened uncertainty, anxiety, and emotionality, individuals high in this trait are more likely to react strongly when faced with contradictions or uncertainty [24]. Our finding is consistent with prior studies indicating that Neuroticism may predict negative emotions, uncertainty, and even avoidance of LLM use [38].

Cognitive Dissonance was generally low to moderate, suggesting that dissonance in LLM use is not universal. Other individual factors (e.g., self-efficacy, cognitive load, and learning motivation) likely contribute to how students perceive LLMs [39].

Surprisingly, H3a revealed a positive and significant mediation effect based on bootstrap confidence intervals, suggesting that higher levels of Neuroticism are associated with higher Technology Acceptance through the experience of Cognitive Dissonance, rather than lower acceptance, as hypothesized. Festinger's theory of dissonance reduction offers a possible explanation: Experiencing Cognitive Dissonance creates psychological tension, which individuals reduce by adjusting their attitudes and behaviors [15]. When expectations regarding LLMs are not met, users may feel anger, frustration, or tension [29]. These negative feelings can be reduced by a change in attitude. This could, for example, be achieved by accepting the technology as a helpful tool in their studies. Coping strategies for dissonance may thus promote acceptance [25]. The positive mediation effect is also in line with the theory of transformative education, which states that learning can be triggered by the experience of irritation and otherness [40]. Both direct and indirect effects between Neuroticism and Technology Acceptance were significant, indicating partial mediation, with Cognitive Dissonance explaining only part of the relationship.

Extraversion showed no significant associations with technology acceptance or LLM usage; therefore, **H3b** was not supported. The direct effect of Extraversion on Technology Acceptance (as suggested in **H1**) was also not significant. The path between Technology Acceptance and LLM Usage was highly significant. Higher acceptance was linked to higher frequency of use among our subjects. However, no direct significant relationship was found between Extraversion and either acceptance or LLM Usage. Thus, Extraversion appears unrelated to the investigated variables. We conclude that while Extraversion does not influence Technology Acceptance of psychology students, Technology Acceptance itself positively predicts LLM Usage, driven by perceptions of usefulness and ease of use [8].

Relatedly, adoption and continued use may depend on users' perceived capability to handle the tool effectively. Differences in digital/AI self-efficacy, AI literacy, and task-related cognitive demands could affect both the experience of dissonance and acceptance and may shape the observed relationships.

B. Interpretation of Exploratory Findings

Exploratory analyses for **H4** suggested a small negative association between Neuroticism and Technology Acceptance. However, the effect was weak and explained only $\approx 2.5\%$ of the variance. While some prior work reports similar negative trends [10], other studies in the context of ChatGPT find no clear relationship [38]. Overall, Neuroticism alone appears to play only a minor role in explaining differences in acceptance [38].

For **H5**, we found no meaningful relationship between Extraversion and Cognitive Dissonance in LLM use; the effect was very small ($\approx 2\%$ explained variance) and statistically negligible.

C. Implications for HCI and Educational Practice

Based on our findings, several implications arise for the design of LLM-supported learning environments in higher education. Students higher in Neuroticism appear more sensitive to negative outcomes when using LLMs. Universities can support responsible use by calibrating expectations about capabilities and limitations, providing transparent rationales and uncertainty cues, scaffolding error recovery with reversible actions and safe defaults, and embedding brief reflective prompts after mismatches. Such measures may reduce emotional strain while promoting informed Technology Acceptance.

The unexpected mediation result, in which Cognitive Dissonance can, under specific conditions, contribute to higher Technology Acceptance, suggests that dissonant experiences can sometimes be turned into learning opportunities when adequately supported. Personality-sensitive design may therefore help tailor feedback and guidance to learners who are particularly vulnerable to contradictory or erroneous information. Personalized scaffolds that reduce Cognitive Dissonance and targeted support for students with higher levels of Neuroticism could help stabilize constructive engagement with these tools.

D. Limitations

Several limitations need to be considered when interpreting our findings.

First, the study relied on a homogeneous sample of psychology students from a single university, most of whom were enrolled in distance study programs. Moreover, most of the participants were females. This focus naturally limits the generalizability of the results to broader populations.

Second, the study followed a correlational, cross-sectional design, which precludes causal conclusions.

Third, Cognitive Dissonance, Technology Acceptance, and LLM Usage were measured with adapted self-report scales that had not originally been validated in the specific context of LLMs. This may reduce construct validity and makes the results susceptible to influences like social desirability or response biases.

Finally, personality was assessed using a shortened version of the BFI-44 that included only the traits Neuroticism and Extraversion, and two Extraversion items were removed to improve reliability. While this yielded acceptable internal consistencies, it narrows content coverage and omits other potentially relevant traits from the Big Five model.

VI. Conclusion and Future Work

In summary, our study contributes to understanding the role of personality in shaping Technology Acceptance of LLMs in higher education. Neuroticism showed small negative associations with acceptance, including a significant negative direct effect in the mediation model. Cognitive Dissonance played a small but theoretically interesting mediating role, indicating that affective reactions may shape acceptance in nuanced ways

Our results highlight the importance of individual differences in human-LLM interaction. Although this interface remains underexplored, our findings underline its relevance from a user perspective and provide a basis for designing adaptive, user-centered AI technologies in educational contexts. Within our student sample, LLM Usage appears to be driven primarily by Technology Acceptance rather than by the examined personality traits, and Neuroticism functions as an indicator for experiencing Cognitive Dissonance rather than as a direct driver of usage.

Our findings yield several implications for future research.

First, longitudinal and experimental studies (e.g., manipulating feedback quality or error frequency) are needed to clarify causal relationships between Neuroticism, Cognitive Dissonance, and Technology Acceptance.

Second, future work should examine more diverse and representative populations beyond psychology students to assess the generalizability of the observed patterns across disciplines and educational settings. In addition, future studies could examine whether group-level adoption climates (e.g., cohort norms or institutional AI policies) aligned with TAM2's social influence mechanisms account for variance beyond individual traits by using multilevel designs. Comparative research across technology classes (e.g., smartphones vs. LLM-based tools) could help distinguish general acceptance mechanisms (e.g., perceived usefulness and ease of use) from effects that are specific to generative AI (e.g., uncertainty and accountability demands due to lack of transparency).

Third, additional Big Five traits (e.g., Openness, Conscientiousness, Agreeableness) and domain-specific, validated instruments should be incorporated to obtain more nuanced assessments of Cognitive Dissonance and LLM Usage. Future work should also include capability-related measures such as AI literacy and digital self-efficacy, and test whether cognitive demands (e.g., task complexity) moderate links between personality, dissonance, and acceptance.

Finally, qualitative and mixed-methods approaches could provide richer insights into users' subjective experiences and emotional reactions, helping to identify specific triggers of dissonance that may not surface in quantitative measures.

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