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Article

Personality Traits and the Technology Acceptance of ChatGPT: Mediating Effects of Perceived Usefulness and Ease of Use

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Abstract: This study investigates how three personality traits from the Big Five framework—extraversion, neuroticism, and conscientiousness—influence individuals' continuance intention to use ChatGPT, with a particular focus on the mediating roles of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Drawing on the Technology Acceptance Model (TAM), this research aims to integrate personality-based differences into a well-established framework for understanding technology adoption and sustained usage. Data were collected through an online survey targeting active ChatGPT users and analyzed using structural equation modeling to examine both direct and indirect relationships among variables. The findings indicate that conscientiousness has a strong and positive impact on both PEOU and PU, and indirectly enhances continuance intention through these cognitive evaluations. Extraversion shows a limited but positive effect primarily through perceived ease of use, suggesting that socially oriented individuals may engage with the system when it is easy to navigate. In contrast, neuroticism does not demonstrate any statistically significant relationship with the key variables in the model. Consistent with TAM, PEOU significantly influences PU and continuance intention, with PU emerging as the most influential predictor of sustained usage. Overall, this study highlights the critical role of conscientiousness in fostering long-term engagement with generative AI systems and underscores the importance of cognitive perceptions in mediating personality effects. By integrating personality psychology with technology acceptance theory, the research provides theoretical and practical implications for designing personalized and adaptive AI interfaces.

Keywords: Personality Traits; Technology Acceptance Model; Perceived Usefulness; Perceived Ease of Use; Continuance Intention; Generative AI; ChatGPT Adoption; Structural Equation Modeling

1. Introduction

The evolution of generative AI has revolutionized human–computer interaction by enabling continuous, dialog-based support rather than mere one-time information retrieval. As a notable example of generative AI, ChatGPT is equipped with a natural language capability that allows users to iteratively refine tasks, which encourages sustained cognitive engagement rather than occasional use. These functionalities and the convenience of generative AI are boosting user productivity in the educational, occupational, and creative spheres, and ChatGPT has been widely adopted for activities such as creating content, programming, learning languages, and customer service provision [1].

However, although ChatGPT has enjoyed rapid diffusion in both educational and professional contexts, there is still limited empirical research examining the psychological mechanisms behind users' intentions to continue using it. Existing empirical evidence from academic and professional contexts has highlighted several cognitive and contextual factors that strongly influence users' adoption of ChatGPT performance expectations, social influences, and facilitating conditions. It has also identified key psychological and experiential drivers of engagement, such as anthropomorphic interaction, perceived trustworthiness, and novel interface design [2,3]. Beyond mere technological adaptation, ChatGPT adoption has been found to be closely associated with users' cognitive appraisals, affective responses, and behavioral intentions [2,3]. Continuance intention (CI) toward ChatGPT has been explained through factors - perceived usefulness, trust, self-efficacy, and ethical awareness. Thus, these factors should be considered essential as generative AI becomes embedded in everyday educational and professional contexts. Research suggests that generative AI systems like ChatGPT will likely become deeply integrated into learning and work environments and, more broadly, that users' cognitive and psychological factors will have a critical role in their technology acceptance and sustained use [3].

Among the theoretical models that have been frequently applied to explain users' acceptance of emerging technologies, the TAM [4] remains one of the most influential. TAM-based [4] research suggests that users' intentions are primarily based on their evaluations of a system's practical value and how much perceived effort is required to effectively utilize it [4,5]. Previous empirical studies have demonstrated that these perceptions exert significant effects on user trust, satisfaction, and willingness to continue adoption, which suggests their important role in understanding how people accept AI-based tools and digital services [6,7]. However, most TAM-based [4] research to date has examined demographic or experiential factors, and relatively few studies have incorporated personality traits as stable psychological antecedents of technology use.

Technology adoption studies conceptualize personality traits as relatively stable individual characteristics that influence how users cognitively interpret and respond to interactive systems [8, 9]. In particular, the traits of extraversion, neuroticism, and conscientiousness have been found to be closely related to technology-related behaviors [10,11] and have been associated with distinct evaluative tendencies toward technology, particularly in relation to interaction style, task structure, and perceived uncertainty. Therefore, by incorporating personality traits into the TAM [4] framework, this study provides a more detailed explanation of how individual differences influence cognitive evaluations and CI in the context of generative AI usage.

Prior studies have also consistently reported that PEOU positively influences PU and that both constructions directly affect CI [5, 6]. For services such as ChatGPT, where consistent and long-term use is inherent, CI is a crucial determinant of sustained effectiveness and user satisfaction [7]. Thus, this study's goals can be summarized as follows: we aim to empirically examine how personality traits—specifically extraversion, neuroticism, and conscientiousness—affect users' use of ChatGPT, to test the interrelationship between these cognitive constructs, and to clarify how they jointly influence users' CI.

2. Literature Review

2.1. Personality Traits and TAM

TAM [4] is a cornerstone theory for understanding how individuals come to adopt and utilize new technologies. In terms of generative AI, PU reflects users' evaluations of whether AI outputs meaningfully support task completion, whereas perceived ease of use relates to how intuitively such interactions can be conducted [4,5]. Specifically, PU reflects the extent to which an individual believes that a system improves task efficiency or performance, whereas PEOU reflects the perception that the system can be operated with little effort. Over the years, the TAM [4] framework has been refined and extended to include additional elements that further explain technology-use behavior, such as social influence, enabling conditions, and personal attributes [12,13]. Particularly in AI-based service contexts, PU and PEOU have been empirically validated as stable predictors of not only initial acceptance but also CI [7].

The Big Five [8] personality dimensions—extraversion, neuroticism, conscientiousness, openness, and agreeableness—have been recognized as enduring psychological dispositions that influence how individuals think, feel, and behave [8]. In technological contexts, extraverted individuals tend to favor technologies that promote social interaction, conscientious users typically engage with systems that enable organized and goal-oriented activity, and individuals high in neuroticism often perceive lower levels of PEOU and PU due to their heightened sensitivity to complexity, uncertainty, and potential risk [10,14]. Recent studies suggest that these traits significantly influence users' acceptance of emerging technologies, including cloud computing, autonomous systems, and generative AI [15–17]. By contrast, agreeableness and openness have shown inconsistent or weak associations with technology acceptance [18,19].

With these points in mind, this study integrates personality traits into the TAM [4] framework to elucidate users' psychological foundations for the adoption and continuance of generative AI tools such as ChatGPT, and we examine the following research question and hypotheses. We aim to provide a more comprehensive understanding of how individuals evaluate and adopt new technologies.

RQ1: Do personality traits (extraversion, neuroticism, conscientiousness) significantly influence PEOU and PU in relation to ChatGPT adoption?

H1a. *Extraversion significantly affects PEOU.*

H1b. *Neuroticism significantly affects PEOU.*

H1c. *Conscientiousness significantly affects PEOU.*

H2a. *Extraversion significantly affects PU.*

H2b. *Neuroticism significantly affects PU.*

H2c. *Conscientiousness significantly affects PU.*

H3a. *Extraversion significantly affects CI.*

H3b. *Neuroticism significantly affects CI.*

H3c. *Conscientiousness significantly affects CI.*

2.2. Cognitive Experiences in Using Generative AI

2.2.1. Perceived Ease of Use in Generative AI

Perceived ease of use (PEOU) indicates the extent to which a person considers a technology to be straightforward and effortless to operate [4]. Within TAM [4], PEOU directly affects continuance intention (CI) and indirectly affects CI through perceived usefulness (PU) [5]. Generative AI systems ensure high usability by enabling natural language-based conversational interaction without requiring complex commands or interfaces [20]. Studies on the ChatGPT tool specifically have demonstrated that its intuitive design and low learning barrier increase users' CIs [21].

2.2.2. Perceived Usefulness of Generative AI

PU refers to the belief that using a particular technology improves work performance or task efficiency [4]. Information systems research consistently identifies PU as one of the strongest predictors of intention to use and has repeatedly confirmed this effect in the context of AI-based services [5,22]. In the case of ChatGPT, users are more likely to continue their use when they perceive improvements in problem-solving speed, idea generation, and content quality [3]. In educational and professional contexts, ChatGPT's ability to create learning materials, translate texts, and support coding contributes to a higher sense of usefulness [21].

2.2.3. Continuance Intention toward Generative AI

Continuance intention (CI), referring to an individual's willingness to continue using technology after initial adoption [6], is considered a key indicator of information system success [23]. Studies grounded in TAM [4] and the expectation–confirmation model (ECM) have identified both PU and PEOU as significant predictors of CI, with PEOU also influencing CI indirectly through PU [5,24]. Research on ChatGPT has similarly demonstrated that PU and PEOU are essential in shaping long-term usage intentions [21].

Taken together, these findings suggest that personality traits influence PEOU and PU, PEOU enhances PU, and both constructs jointly predict CI. Accordingly, this study examines the effects of PEOU and PU on CI through the following research question and hypotheses.

RQ2: Do PEOU and PU significantly affect CI in the context of ChatGPT adoption?

H4. *PEOU significantly affects perceived usefulness.*

H5. *PEOU significantly affects CI.*

H6. *PU significantly affects CI.*

2.3. Mediating Effects of Personality Traits on Cognitive Experience

According to the TAM [4], the sequential mediation path of PEOU → PU → intention to use represents a central mechanism in technology acceptance [4, 5]. In other words, perceiving a technology as easy to use leads to perceiving it as useful, which ultimately strengthens the intention to continue using it. Prior research has further demonstrated that Big Five [8] personality traits influence behavioral intentions not directly but indirectly through their effects on users' cognitive evaluations of technology (i.e., formation of PU and PEOU) [25,26]. Thus, this study examines research questions and hypotheses.

RQ3: In relation to ChatGPT adoption, do personality traits significantly affect CI through the mediating effects of PEOU and PU?

H7a. *Extraversion affects CI through the mediation of PU.*

H7b. *Neuroticism affects CI through the mediation of PU.*

H7c. *Conscientiousness affects CI through the mediation of PU.*

H8a. *Extraversion affects CI through the mediation of PU.*

H8b. *Neuroticism affects CI through the mediation of PU.*

H8c. *Conscientiousness affects CI through the mediation of PU.*

Furthermore, the Big Five [8] traits may influence CI through sequential mediation in which PEOU affects PU which, in turn, affects CI [25, 26]. We expect that personality traits predict CI indirectly through users' cognitive evaluations of generative AI. Accordingly, this study examines research questions and hypotheses.

RQ4: In relation to the ChatGPT adoption, do personality traits influence CI through the sequential mediation of PEOU and perceived usefulness?

H9. *PEOU affects CI through the mediation of PU.*

H10a. *Extraversion affects CI through the sequential mediation of PEOU and PU.*

H10b. *Neuroticism affects CI through the sequential mediation of PEOU and PU.*

H10c. *Conscientiousness affects CI through the sequential mediation of PEOU and PU.*

As shown in **Figure 1**, this study's conceptual framework combines the Big Five [8] personality dimensions with the TAM [4] to investigate both the direct and indirect influences on users' intention to continue engaging with ChatGPT.

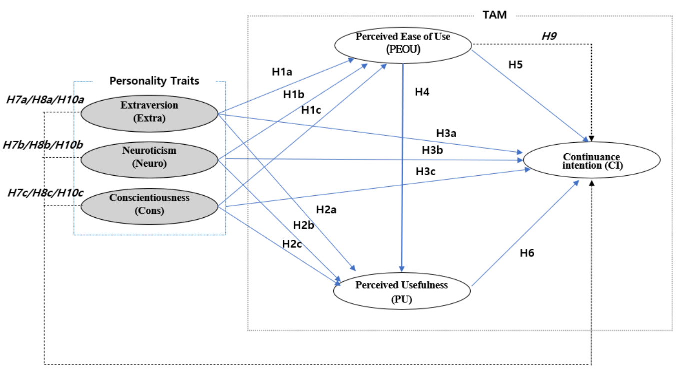

Figure 1. Research model.

Note: Dashed lines indicate mediating effects.

3. Methodology

3.1. Participants and Data Collection

3.1.1. Survey Design

The survey instrument was developed based on measurement items that had been previously validated for reliability and construct validity in a pilot study. The survey was administered in an online format accessible via both mobile and desktop. The final questionnaire comprised 91 items, and participants were informed in advance about the study's purpose and data protection policy. All responses were collected anonymously, and the survey system automatically excluded missing and duplicate entries. All items were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The questionnaire comprised four main sections. The first section included items on respondents' demographic characteristics and ChatGPT usage patterns (e.g., usage frequency and purpose). The second measured users' cognitive and attitudinal factors, including satisfaction, perceived usefulness, perceived ease of use, and CI. The third section addressed psychological and social influence factors, such as information characteristics, personality traits, emotional responses, trust, risk perception, and social influence. Finally, the fourth section included supplementary background questions and closing items for auxiliary analysis.

3.1.2. Sampling Procedure and Participants

The target population of this study comprised Korean university students with prior experience using ChatGPT. A structured online survey was administered by a professional research agency, Micro Embrain Co., Ltd., which specializes in large-scale academic and market research. To ensure representativeness, a stratified quota sampling method was employed based on age, gender, and regional distribution.

A total of 280 valid responses were obtained after excluding incomplete or invalid cases. Only participants who met the predefined screening criteria—confirming prior ChatGPT usage and consistent response patterns—were included in the final analysis dataset.

3.2. Measurement Variables and Operational Definitions

The principal latent variables in this research were conceptualized with reference to well-established theoretical foundations and prior empirical findings. The measurement indicators were carefully modified and tailored to reflect the specific context of this study, maintaining both theoretical consistency and linguistic precision. Each item was assessed using a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree).

PEOU and PU were measured using items adapted from the TAM developed by Davis [4] and subsequent extensions. CI was assessed following Expectation–Confirmation Model of Information System Continuance (ECM-IS) [6].

Personality traits were measured using selected items representing extraversion, neuroticism, and conscientiousness from the Big Five [8] Personality Framework [8,9]. The operational definitions, number of items, measurement scales, and original sources for each construct are summarized in **Appendix Table A1**.

3.3. Data Analysis Procedure

3.3.1. Data Preprocessing

All statistical procedures were performed using Stata/MP version 18.0. Before testing the hypotheses, the dataset was screened for missing observations and outliers, and descriptive statistics were generated to summarize the sample characteristics. Potential multicollinearity among the predictor variables was evaluated by computing the variance inflation factor (VIF) scores. The obtained VIF values ranged from 1.06 to 2.64, which are considerably lower than the conventional cutoff value of 5.0 suggested by Hair et al. [27], confirming that multicollinearity does not pose an issue in this study.

3.3.2. Measurement Model Evaluation

A confirmatory factor analysis (CFA) was conducted to evaluate the internal consistency, construct reliability, and convergent and discriminant validity of the measurement model [28]. The reliability of each construct was regarded as adequate when the values of Cronbach's alpha and composite reliability (CR) were above the recommended benchmark of 0.70 [27,29]. Evidence of convergent validity was established when all standardized factor loadings exceeded 0.70 and the average variance extracted (AVE) was greater than 0.50 [27,30]. To examine discriminant validity, two complementary criteria were applied: the Fornell–Larcker criterion [31] and the heterotrait–monotrait ratio (HTMT) [32]. Consistent with previous methodological guidelines, discriminant validity was considered satisfactory if HTMT estimates were below 0.85 and their confidence intervals did not include 1 [32,33].

3.3.3. Structural Model Analysis

The structural equation model (SEM) was estimated using the maximum likelihood (ML) method. Model fit was evaluated using multiple indices—χ^2, root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker–Lewis's index (TLI), and standardized root mean square residual (SRMR)—applying the conventional cut-off criteria (CFI/TLI $\geq$ 0.90, RMSEA $\leq$ 0.08, SRMR $\leq$ 0.08) [34]. Where necessary, modification indices (MI $\geq$ 10) were reviewed to improve model fit by adding theoretically justified paths or covariances among error terms. Mediation effects were tested using a bootstrapping approach with 5,000 resamples at a 95% confidence interval [35]. Indirect effects were estimated using the nlcom command in Stata. The results reported standardized path coefficients, explained variance (R^2), and VIF values for each endogenous construct.

4. Results and Discussion

4.1. Descriptive Statistics

A total of 280 respondents participated in this survey, with an equal gender distribution of 140 males (50.0%) and 140 females (50.0%). Most respondents were between 21 and 23 years old (46.4%), while the smallest group was aged 27–29 years (1.8%). The sample was evenly distributed across academic years, with 25% from each of the four years of study. Regarding ChatGPT usage patterns, 246 participants (87.9%) reported using the free version, whereas 34 participants (12.1%) were paid subscribers. Regarding the number of ChatGPT-related services used, 51.1% of respondents indicated using one service, followed by two services (30.4%), three (12.9%), four (3.6%), and five (2.1%). Detailed demographic information is presented in **Table 1**.

Table 1. Sample characteristics.

Variable	Frequency (%)
Gender	
Male	140 (50.0%)
Female	140 (50.0%)
Age	
18–20 years	106 (37.9%)
21–23 years	130 (46.4%)
24–26 years	39 (13.9%)
27–29 years	5 (1.8%)
Undergraduate year	
Freshman (1st year)	70 (25%)
Sophomore (2nd year)	70 (25%)
Junior (3rd year)	70 (25%)
Senior (4th year)	70 (25%)
Subscription status	
Free	246 (87.9%)
Paid	34 (12.1%)
No. of services	
1	143 (51.1%)
2	85 (30.4%)
3	36 (12.9%)
4	10 (3.6%)
5	6 (2.1%)

The correlation matrix among the major variables and discriminant validity results are presented in **Table 2**. CI was found to be strongly and positively correlated with both PEOU (r = 0.565, p < 0.01) and PU (r = 0.758, p < 0.01), consistent with the theoretical premise of the TAM [4] that users' perceptions of usefulness and ease of use increase their intention to continue using technology. In addition, a significant positive correlation was observed between PEOU and PU (r = 0.604, p < 0.01), consistent with prior findings suggesting that PEOU positively influences PU.

Table 2. Descriptive statistics, reliability, and validity results of constructs (N = 280).

Construct/Items	Mean	SD	Factor Loading	Cronbach's α	CR	AVE
CI						
q34	4.35	0.71	0.84	0.87	0.86	0.63
q35	4.29	0.73	0.86			
q36	3.99	0.89	0.77			
q37	3.89	0.88	0.70			
PEOU						
q30	4.27	0.67	0.76	0.83	0.87	0.62
q31	4.15	0.80	0.74			
q32	4.19	0.72	0.85			
q33	4.25	0.67	0.83			
PU						
q26	4.17	0.69	0.83	0.87	0.82	0.52
q27	4.15	0.78	0.73			
q28	4.29	0.78	0.74			
q29	3.91	0.78	0.67			
Extraversion						
q43	3.12	1.09	0.78	0.90	0.90	0.68
q44	3.25	1.09	0.87			
q45	3.13	1.13	0.84			
q46	3.13	1.08	0.82			
Neuroticism						
q47	3.30	1.20	0.77	0.79	0.80	0.51
q48	3.53	1.10	0.66			
q49	2.67	1.15	0.76			
q50	2.41	1.19	0.62			
Conscientiousness						
q60	3.56	0.89	0.68	0.77	0.74	0.56
q61	3.84	0.89	0.81			
q62	3.96	0.72	0.74			
Agreeableness						
q63	3.36	1.02	0.61	0.60	0.61	0.34
q64	3.79	0.81	0.48			
q65	3.42	0.91	0.66			
Openness						
q56	3.40	0.98	0.54	0.69	0.70	0.38
q57	4.09	0.71	0.59			
q58	4.03	0.77	0.50			
q59	3.71	0.91	0.80			

Note: CR = composite reliability; AVE = average variance extracted.

Regarding personality traits, extraversion showed significant positive correlations with CI (r = 0.126, p < 0.05), PEOU (r = 0.211, p < 0.01), and PU (r = 0.153, p < 0.05). Neuroticism, however, was not significantly correlated with PU, PEOU, or CI but exhibited a negative association with conscientiousness (r = –0.215, p < 0.01). Conscientiousness demonstrated significant positive correlations with CI (r = 0.286, p < 0.01), PU (r = 0.275, p < 0.01), and PEOU (r = 0.267, p < 0.01), which suggests that individuals with higher conscientiousness tend to evaluate technologies more positively and display stronger CIs.

Overall, the observed correlation patterns among the constructs were consistent with the theoretical expectations derived from the TAM [4] and personality trait frameworks, thereby supporting the proposed conceptual model.

4.2. Measurement Model Evaluation

4.2.1. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was conducted to examine the measurement validity of each latent construct. All factor loadings were statistically significant (p < 0.001), and most exceeded 0.70, thereby confirming adequate convergent validity. The reliability and validity indices also met the recommended thresholds: most constructs demonstrated Cronbach's alpha ≥ 0.70, CR ≥ 0.70, and AVE ≥ 0.50, consistent with the guidelines proposed by Hair et al. [27].

4.2.2. Survey Design

Among the personality traits, agreeableness and openness did not meet the acceptable thresholds for Cronbach's alpha, CR, or AVE [27,31], which indicates insufficient internal consistency and convergent validity. Accordingly, the final measurement model retained only extraversion, neuroticism, and conscientiousness as personality trait constructs. Cronbach's alpha coefficients for all retained constructs ranged from 0.77 to 0.90, demonstrating high reliability. CR values ranged from 0.74 to 0.87, exceeding the minimum acceptable level of 0.70, while AVE values ranged from 0.51 to 0.68, surpassing the 0.50 threshold [31]. These results collectively indicate the satisfactory internal consistency and convergent validity of the measurement scales. Descriptive statistics, factor loadings, Cronbach's alpha, CR, and AVE values for each latent construct are summarized in **Table 2**.

4.2.3. Discriminant Validity

To assess discriminant validity, the Fornell–Larcker criterion was applied [31]. Specifically, the square root of the AVE for each latent construct was compared with its corresponding inter-construct correlation coefficients. As shown in **Table 3**, the square roots of all AVE values were greater than their respective inter-construct correlations, indicating satisfactory discriminant validity for the measurement model. These results suggest that each construct shares more variance with its own indicators than with other constructs, thereby supporting the distinctiveness of the latent variables.

Table 3. Discriminant validity using the Fornell and Larcker criterion.

Construct	CI	PEOU	PU	Extra	Neuro	Cons
CI	0.794					
PEOU	0.565***	0.787				
PU	0.758***	0.604***	0.721			
Extra	0.126**	0.211***	0.153**	0.825		
Neuro	−0.064	−0.085	−0.064	−0.003	0.714	
Cons	0.286***	0.267***	0.275***	0.417***	−0.215***	0.748

Note: CI = continuance intention; PEOU = perceived ease of use; PU = perceived usefulness; Extra = extraversion; Neuro = neuroticism; Cons = conscientiousness. ** $p < 0.05$, *** $p < 0.01$.

In addition, the heterotrait–monotrait ratio (HTMT) values for all construct pairs were computed and are presented in **Table 4**. Most HTMT values ranged from 0.096 to 0.543, while the relationship between CI and PU yielded a value of 0.897. Nevertheless, this value remains below the conservative threshold of 0.90 recommended by Henseler et al. [32], thereby satisfying the criterion for discriminant validity.

Taken together, the results from both the Fornell–Larcker criterion and HTMT analysis consistently demonstrate that the measurement model possesses adequate discriminant validity among all latent constructs.

Table 4. HTMT criterion.

Construct	CI	PEOU	PU	Extra	Neuro	Cons
CI	—	0.619	0.897	0.146	0.096	0.363
PEOU		—	0.703	0.188	0.103	0.364
PU			—	0.237	0.112	0.336
Extra				—	0.103	0.543
Neuro					—	0.296
Cons						—

Note: CI = continuance intention; PEOU = perceived ease of use; PU = perceived usefulness; Extra = extraversion; Neuro = neuroticism; Cons = conscientiousness.

4.3. Model Fit and Hypothesis Testing

4.3.1. Model Fit

The overall goodness-of-fit indices for the structural equation model (SEM) indicated that the proposed research model demonstrated an acceptable fit to the data. Compared with the saturated model, the chi-square statistic was $\chi^2(210) = 397.541$ ($p < 0.001$), and the normalized chi-square (χ^2/df) value was 1.89, which falls within the acceptable range [14,36]. Both absolute and incremental fit indices were also examined. The results showed the following values: RMSEA = 0.056, CFI = 0.945, TLI = 0.931, and SRMR = 0.042. All satisfy the commonly recommended thresholds (RMSEA ≤ 0.08, CFI/TLI ≥ 0.90, SRMR ≤ 0.08) [37,38]. Accordingly, the structural model was considered to exhibit a statistically adequate level of model fit, supporting the suitability of the proposed theoretical framework for further hypothesis testing (**Table 5**).

Table 5. Key fit indices of the structural equation model.

Index	Value	Criterion	Interpretation
χ^2 (df = 210)	397.541	Smaller = better fit	-
χ^2/df	1.89	≤ 3 acceptable, ≤ 2 excellent	Acceptable
RMSEA[90% CI]	0.057[0.048–0.06]	≤ 0.06 good, 0.06–0.08 acceptable	Acceptable
pclose	0.101	≥ 0.05	
CFI	0.947	≥ 0.95 good	Good
TLI	0.936	≥ 0.90 acceptable, ≥ 0.95 excellent	Excellent
SRMR	0.060	≤ 0.08 acceptable (≤ 0.05 excellent)	Acceptable
AIC	13,387.705	For model comparison	-
BIC	13,711.201	For model comparison	-
CD	0.995	Closer to 1 = higher explanatory power	Very high explanatory power

Note: RMSEA = root mean square error of approximation; CFI = comparative fit index; TLI = Tucker–Lewis index; SRMR = standardized root mean square residual; AIC/BIC = information criteria used for model comparison; CD = coefficient of determination.

4.3.2. Hypothesis Testing

To empirically verify the hypothesized relationships among latent constructions, SEM analysis was performed using Stata 18. Standardized path coefficients and confidence intervals were estimated through 5,000 bootstrap resamples. The results of the direct effect analysis are summarized in **Table 6**.

Table 6. Direct effect and hypothesis testing.

Hypothesis	Path	β(Std)	*SE*(Boot)	*z*	*p*	Supported	R^2(R^2_{adj})
H1a	Extra → PEOU	0.040	0.061	0.380	0.701	✗	0.110(0.101)
H1b	Neuro → PEOU	0.015	0.033	0.230	0.820	✗	
H1c	Cons → PEOU	0.315*	0.104	2.330	0.020	○	
H2a	Extra → PU	−0.094	0.061	−1.020	0.307	✗	0.517(0.510)
H2b	Neuro → PU	−0.022	0.034	−0.360	0.721	✗	
H2c	Cons → PU	0.211	0.099	1.820	0.069	△	
H4	PEOU → PU	0.649*	0.103	7.010	0.000	○	
H5	PEOU → CI	−0.001	0.145	−0.010	0.991	✗	0.787(0.783)
H6	PU → CI	0.885*	0.150	6.120	0.000	○	
H3a	Extra → CI	−0.054	0.053	−0.700	0.485	✗	
H3b	Neuro → CI	0.037	0.030	0.710	0.477	✗	
H3c	Cons → CI	0.036	0.082	0.390	0.699	✗	

Note: CI = continuance intention; PEOU = perceived ease of use; PU = perceived usefulness; Extra = extraversion; Neuro = neuroticism; Cons = conscientiousness. *p < 0.05. "○" indicates support, "✗" indicates rejection, and "△" indicates marginal support at the 0.1 significance level (p = 0.069).

Regarding the effects of personality traits on perceived ease of use, conscientiousness (Cons → PEOU) exhibited a significant positive effect (β = 0.315, p = 0.020), whereas extraversion (Extra → PEOU) and neuroticism (Neuro → PEOU) were not significant. Accordingly, H1c was supported, while H1a and H1b were rejected. Regarding the effects of personality traits on perceived usefulness, conscientiousness (Cons → PU) also showed a positive influence (β = 0.211, p = 0.069), whereas extraversion and neuroticism remained non-significant. Thus, H2c was supported, and H2a and H2b were rejected. The hypothesized relationship between PEOU and PU (H4) was strongly supported (β = 0.649, p < 0.001), which reaffirms a central assumption of the TAM [4]. By contrast, none of the direct effects of personality traits on CI were statistically significant.

4.3.3. Mediating Effects of PEOU and PU: Indirect and Total Effects

To examine the mediating roles of PEOU and PU in the relationship between users' personality traits and their CI toward ChatGPT, we estimated direct, indirect, and total effects using the estat teffects command in Stata 18. The statistical significance of indirect effects was verified through 5,000 bootstrap resamples with bias-corrected and accelerated (BCa) 95% confidence intervals. The detailed results are presented in **Table 7**.

Table 7. Indirect and total effects (standardized coefficients, bootstrapped 5,000 samples, N = 280).

Hypothesis	Path	Indirect Effects					Total Effects			
		β(Std)	*SE*	*z*	*p*	95% CI	β(Std)	*SE*	*z*	*p*
H7a	Extra → PU → IU	−0.06	0.07	−0.62	0.54	[−0.17, 0.09]	−0.11	0.07	−1.20	0.23

Table 7. *Cont.*

Hypothesis	Path	Indirect Effects β(Std)	*SE*	*z*	*p*	95% CI	Total Effects β(Std)	*SE*	*z*	*p*
H7b	Neuro → PU → IU	−0.01	0.04	−0.17	0.86	[−0.08, 0.06]	0.03	0.03	0.43	0.67
H7c	Cons → PU → IU	0.37^{***}	0.11	2.97	0.00	[0.11, 0.54]	0.40^{***}	0.11	3.18	0.00
H8a	Extra → PEOU → IU	≈ 0.00	0.01	−0.01	0.99	[−0.01, 0.01]	−0.05	0.05	−0.70	0.49
H8b	Neuro → PEOU → IU	≈ 0.00	0.00	−0.01	0.99	[−0.00, 0.00]	0.04	0.03	0.71	0.48
H8c	Cons → PEOU → IU	≈ 0.00	0.05	−0.01	0.99	[−0.09, 0.09]	0.04	0.08	0.39	0.70
H9	PEOU → PU → IU	0.57^{***}	0.16	4.23	0.00	[0.36, 0.97]	0.57^{***}	0.11	6.12	0.00
H10a	Extra → PEOU → PU → IU	−0.06	0.07	−0.62	0.54	[−0.17, 0.09]	−0.11	0.07	−1.20	0.23
H10b	Neuro → PEOU → PU → IU	−0.01	0.04	−0.17	0.86	[−0.08, 0.06]	0.03	0.03	0.43	0.67
H10c	Cons → PEOU → PU → IU	0.37^{***}	0.11	2.97	0.00	[0.11, 0.54]	0.40^{***}	0.11	3.18	0.00

Note: Bootstrap standard errors were estimated with 5,000 resamples, and 95% bias-corrected accelerated (BCa) confidence intervals are reported. CI = continuance intention; PEOU = perceived ease of use; PU = perceived usefulness; Extra = extraversion; Neuro = neuroticism; Cons = conscientiousness. ***$p < 0.001$.

The mediation analysis revealed that conscientiousness exerted a significant indirect effect on CI through PU (β = 0.37, $p < 0.01$). This finding indicates that highly conscientious users tend to perceive ChatGPT as more useful, which, in turn, strengthens their intention to continue using it. By contrast, extraversion and neuroticism did not show significant indirect effects through PU.

The sequential mediation path of PEOU → PU → CI was strongly supported (β = 0.57, $p < 0.001$). This finding confirms the central mechanism proposed by the TAM [4] that ease of use enhances perceived usefulness, which subsequently increases CI. Furthermore, conscientiousness demonstrated a significant sequential indirect effect on CI through both PEOU and PU (H10c, β = 0.37, $p < 0.01$), whereas the sequential effects of extraversion and neuroticism were not significant.

Overall, the findings indicate that conscientiousness exerts both single and sequential mediation effects through PU and PEOU, establishing it as a key personality factor that influences users' sustained engagement with ChatGPT.

Figure 2 presents the standardized path coefficients across all hypothesized paths, with standardized path coefficients indicating the strength and significance of each relationship among the constructs.

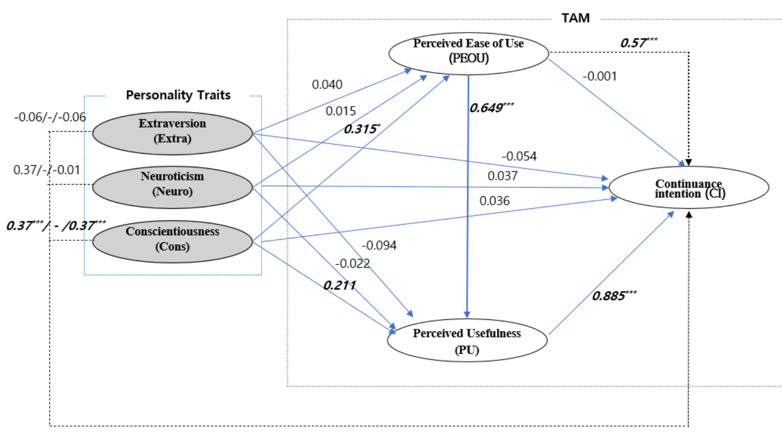

Figure 2. Structural Model Estimation Results.

Note: Dashed lines indicate mediating effects.

5. Conclusions

5.1. Theoretical Implications

This study shows the theoretical understanding of technology acceptance by integrating personality traits with key TAM [4] constructs and reconceptualizing the TAM [4] as a cognitive appraisal process that is contingent on individual personality traits in the context of generative AI.

First, beyond simply reaffirming the TAM's [4] core pathways, our findings refine its internal logic by identifying context-specific boundary conditions. While the sequential pathway remains central, we find that PEOU functions not as an independent determinant of CI but rather as a foundational condition that enables users' evaluation of the service's usefulness. In the generative AI context, where users must interpret and evaluate AI-generated outputs, ease of use contributes to sustained usage only insofar as it enables the recognition of task-related value. Thus, our findings contextualize the sequential mediation pathway as a value-construction mechanism rather than a direct motivational route and expand our understanding of how the TAM [4] applies to cognitively demanding AI systems [4,5,12].

Second, this study elucidates the cognitive mediation structure linking personality and technology acceptance by demonstrating that personality traits function as indirect cognitive modulators rather than direct behavioral drivers. Conscientiousness was found to influence CI through PU and the sequential cognitive pathway, which suggests that individual differences determine how users cognitively translate system characteristics into perceived value. Rather than having a direct effect on CI, conscientiousness appears to foster goal-oriented, structured, and effortful engagement with generative AI, which then strengthens the evaluative processes related to usefulness. These findings are consistent with those of prior research [11,14] and provide empirical justification for extending the TAM [4] to include personality-based antecedents at the cognitive level.

Third, the differential effects of personality traits indicate that the person–technology fit is crucial in users' adoption of generative AI. While the lack of meaningful effects observed for extraversion and neuroticism suggests that traits associated with social stimulation or emotional sensitivity are less relevant in task-oriented and cognitively structured AI interactions, conscientiousness appears to be closely associated with the functional features of generative AI. This differentiation implies that personality traits activate distinct cognitive evaluation pathways depending on the technological context.

Overall, this study's integration of personality traits and TAM [4] constructs represents a theoretical extension of technology acceptance research by shifting the focus from uniform acceptance mechanisms to personality-contingent cognitive appraisal processes and by demonstrating that the sustained adoption and use of generative AI technologies can be best explained using a framework that accounts for individual differences and value-based cognitive evaluations.

5.2. Practical Implications

By translating the mechanisms of cognitive acceptance into actionable principles for design and management, our findings offer practical implications for the design, operation, and management of generative AI services such as ChatGPT. First, the user experience should be designed so that PEOU naturally translates into perceived usefulness; in this way, PEOU can serve as a catalyst for usefulness recognition rather than an end. However, simplifying interfaces alone may not ensure user retention, as sustained usage occurs only when usability enhances users' cognitive evaluation of task value. Thus, practical design strategies should prioritize features that communicate value, such as task-specific templates, example prompts, transparent explanations of results, rationale displays, and automated follow-up questions, which can help users cognitively connect system outputs to task outcomes.

Second, the strong influence of conscientiousness suggests a need to implement personality-informed personalization strategies. Conscientious users tend to favor structured workflows, goal-oriented interactions, and performance feedback; therefore, features such as progress tracking, achievement-based milestones, and visualized feedback systems can encourage these users' sustained engagement by aligning with their cognitive self-regulation tendencies. To this end, adaptive interface architectures are needed that can dynamically adjust feedback and interaction logic in accordance with individual cognitive and motivational profiles.

Third, the limited influence of extraversion and neuroticism suggests that psychological and cognitive segmentation may be more effective than traditional demographic methods when managing generative AI users. While extraverted users may appreciate optional community or collaborative features, users with higher neurotic tendencies may respond more positively to design elements that enhance clarity, such as procedural guidance, credibility cues, and uncertainty-reducing interface signals, which can provide cognitive reassurance rather than emotional stimulation.

Fourth, the mediating roles of PEOU and PU suggest that, to promote generative AI adoption, optimizing usability must be balanced with explicit value communication. For ChatGPT, improving interface intuitiveness, increasing response speed, and minimizing hallucinations should be complemented by contextualized use cases, domain-specific success stories, and application scenarios to ensure that usefulness is cognitively salient and experientially verifiable.

Finally, regarding policy implications, this study emphasizes that as generative AI technologies become ubiquitous, human-centered AI governance frameworks that consider personality and cognitive diversity are critical. Policymakers should, therefore, develop AI design guidelines that incorporate psychological and cognitive factors, and organizations should adopt user-specific training, support, and engagement strategies that promote responsible, inclusive, and sustained AI use.

5.3. Limitations and Future Research

While this study seems to offer both theoretical insights and practical implications, several limitations should be acknowledged. First, our reliance on cross-sectional data restricts our ability to infer causal relationships or examine temporal dynamics among personal characteristics, PEOU, PU, and CI. Future research should adopt longitudinal or experimental designs to identify causal mechanisms and changes in technology use behavior over time [39].

Second, this study examines a single national sample of Korean users, which may limit the generalizability of the findings to other cultural contexts. Given that technology acceptance and personality expression vary based on cultural values, social norms, and learning environments [40], future studies should replicate and validate this study's proposed model across diverse cultural, national, and organizational settings.

Finally, this study includes only three of the Big Five [8] personality traits—extraversion, neuroticism, and conscientiousness—as openness and agreeableness did not meet the required reliability and validity criteria. Future research should incorporate all five personality dimensions or examine context-relevant sub-traits, such as self-regulation, mastery orientation, or cognitive openness, that may be particularly salient in the context of generative AI usage.

Looking ahead, future research could further expand the proposed framework through cross-cultural comparisons, longitudinal studies of behavioral continuity, and model extensions that investigate additional mediating or moderating variables. These efforts would deepen our understanding of what sustains engagement with generative AI and how to optimize user experience design and would enable the development of more effective management and governance strategies for AI-based platforms [39,40].

Author Contributions

Conceptualization, H.S.H. and S.K.; methodology, S.K.; validation, H.S.H. and S.K.; formal analysis, S.K.; writing—original draft preparation, S.K.; writing—review and editing, H.S.H.; supervision, H.S.H. Both authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data are available upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

AI Use Statement

The authors used ChatGPT (version 5.2) solely for grammar checking, sentence structure refinement, and improving the readability of the English text in this manuscript. The authors take full responsibility for all academic content, including all ideas, data, analyses, and conclusions presented herein. The use of AI was thoroughly reviewed and supervised by the authors.

Appendix A

Table A1. Measurement scales of the model.

Construct, Operational Definition, and Measurement Items	Sources
Continuance intention (CI) *Definition:* The degree to which an individual intends to continue using ChatGPT. 1) I intend to continue using ChatGPT. 2) I expect to make frequent use of ChatGPT going forward. 3) I plan to continue utilizing ChatGPT in the near future. 4) I anticipate that my use of ChatGPT will increase over time compared to my current level.	Siu and White [19]; Polyportis and Pahos [21]; Almogren et al. [41]
Perceived ease of use (PEOU) *Definition:* The extent to which a person perceives ChatGPT as simple to operate and easy to understand. 1) ChatGPT is easy to learn. 2) Using ChatGPT requires minimal mental effort. 3) Overall, I think ChatGPT is user-friendly. 4) ChatGPT is convenient and faster.	Davis [4]; Kim et al. [42]; Sallam [43]
Perceived usefulness (PU) *Definition:* The extent to which a person perceives the use of ChatGPT as advantageous and valuable. 1) ChatGPT is useful. 2) ChatGPT can help me find the information I need quickly. 3) ChatGPT assists my work/study. 4) ChatGPT helps improve my productivity.	Davis [4]; Venkatesh et al. [12]; Sallam [43]
Extraversion *Definition:* The degree to which an individual engages in interpersonal interaction, exhibits high levels of activity, seeks stimulation, and demonstrates the ability to have fun. 1) I would rate myself as a talkative individual. 2) I consider myself an energetic and outgoing person. 3) I enjoy spending time interacting with others. 4) I generally prefer to take the lead in group activities.	Sallam [43]; Lakhal and Khechine [44]
Neuroticism *Definition:* The extent to which an individual tends to experience emotional instability, hold unrealistic expectations, and employ maladaptive coping strategies. 1) I am more sensitive than most other people. 2) I frequently find myself worrying about something. 3) I often experience periods of loneliness. 4) I sometimes feel "just miserable" for no good reason at all.	Sallam [43]; Lakhal and Khechine [44]
Conscientiousness *Definition:* The degree to which an individual demonstrates organization, perseverance, and motivation in goal-oriented behavior 1) I consider myself a person who approaches tasks carefully and completes them diligently. 2) I tend to focus on specific details when pursuing objectives. 3) I make sure to be well-organized and ready when performing assigned tasks.	Lakhal and Khechine [44]; Rammstedt and John [45]
Agreeableness *Definition:* The extent to which a person's social orientation varies from kindness and empathy to hostility in thoughts, emotions, and behaviors. 1) I generally trust others. 2) I tend to be honest in everything I do. 3) I think of others before myself.	Rammstedt and John [45]
Opennness *Definition:* The degree to which an individual proactively seeks information, values experiential learning, tolerates ambiguity, and engages in exploratory behavior. 1) Individuals high in openness tend to enjoy exploring creative and unconventional approaches to problem-solving. 2) I enjoy cultural activities and leisure. 3) I respect opinions that are different from mine. 4) I enjoy new experiences.	Rammstedt and John [45]

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