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The personality profile of early generative AI adopters: a big five perspective

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Abstract

Purpose – This pilot study aimed to evaluate the impact of the big five personality traits on user engagement with chatbots at the early stages of artificial intelligence (AI) adoption.
Design/methodology/approach – The pilot study involved 62 participants segmented into two groups to measure variables including engagement duration, task performance and future AI usage intentions.
Findings – The findings advocate for the incorporation of psychological principles into technology design to facilitate more tailored and efficient human–AI collaboration.
Originality/value – This pilot research study highlights the relationship between the big five personality traits and chatbot usage and provides valuable insights for customizing chatbot development to align with specific user characteristics. This will serve to enhance both user satisfaction and task productivity.

Keywords Human–AI collaboration, Generative AI, Personality traits, Big five, AI adoption, Chatbot

Paper type Research paper

Introduction

Artificial intelligence has become an integral part of modern workplaces. It revolutionized task performance across various industries (Paschen, Pitt, & Kietzmann, 2020) (Hart-Davis, 2023). Despite the widespread adoption, we should remember that employees are not a homogeneous group; i.e. each individual brings a unique set of traits and preferences to their interactions with technology (Przegalinska & Triantoro, 2024). This diversity suggests the need for a nuanced approach to AI implementation, which considers the varied human elements in the workplace (Ludik, 2021; Cebulla, Szpak, & Knight, 2023).

Prior studies show that AI affects human labor in creative tasks, noting that automation can either increase or decrease labor demand depending on task complementarity (Brynjolfsson & Mitchell, 2017). Eloundou, Manning, Mishkin, and Rock (2023) estimate that large language models (LLMs) could impact at least 10% of tasks for 80% of US workers, with 19% potentially seeing over 50% of their tasks affected. Eloundou *et al.* (2023) suggest that LLMs could significantly accelerate about 15% of US worker tasks. Dell'Acqua *et al.* (2023)

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demonstrated AI's productivity benefits in an experiment with 758 consultants, showing GPT-4's improved task speed and quality. This supports the "jagged technological frontier" concept, according to which AI excels in specific tasks and benefits workers across skill levels.

The big five personality traits model is a widely accepted framework for evaluating human personality. It offers a valuable lens through which to examine the adoption of AI (Triantoro & Przegalińska, 2022). This model categorizes personality into five broad dimensions: openness, conscientiousness, extraversion, agreeableness and neuroticism (McCrae & John, 1992). Understanding how these traits influence the way individuals engage with generative AI can provide critical insights into designing more effective AI-based information systems and interfaces (Yorks, Rotatori, Sung, & Justice, 2020).

In this pilot research, we aimed to explore the relationship between the big five personality traits (De Raad, 2000) and employee interactions with generative AI technologies. By examining a range of tasks that vary in complexity and creativity, we sought to identify how personality differences affected the use and perception of generative AI tools. We based this investigation on a proposition that personality traits can significantly impact how employees interact with AI, potentially influencing their efficiency, creativity and overall satisfaction with AI-enabled processes.

We expect the findings to contribute to the development of more personalized and user-friendly AI applications in the workplace. By tailoring AI technologies to better fit users' psychological profiles, organizations can enhance user engagement, improve task performance and foster a more productive and harmonious human–AI collaboration.

The big five personality theory

The big five personality theory posits that five broad dimensions capture the most significant variations in human personality (Roccas, Sagiv, Schwartz, & Knafo, 2002). These dimensions include openness, conscientiousness, extraversion, agreeableness and neuroticism. Collectively, we refer to them by the acronym OCEAN. Scholars widely use this framework in psychological research for predicting behavior, preferences and interactions in various contexts, including work environments and technology usage (Triantoro, Gopal, Benbunan-Fich, & Lang, 2019, 2020).

Openness means a person's willingness to experience a variety of activities and their intellectual curiosity (Roccas *et al.*, 2002). Typically, individuals high in openness display imagination, curiosity about both the inner and outer worlds, and willingness to try new things, including innovative technologies. They may be more inclined to explore and embrace AI tools, showing a predisposition to experiment with novel AI functionalities.

Conscientiousness reflects a person's self-discipline, carefulness and dependability (Roccas *et al.*, 2002). Highly conscientious individuals are organized, methodical and responsible. They might prefer AI systems that enhance productivity, offer structured guidance and help in managing tasks efficiently, reflecting a preference for reliable and practical AI solutions.

Extraversion features outgoingness, sociability and an energetic approach to the social and material world (Roccas *et al.*, 2002). Typically, extraverts appreciate AI chatbots that we may refer to as interactive, engaging and mimic human-like communication patterns, facilitating a more enjoyable and dynamic interaction experience.

Agreeableness indicates a person's altruism, trust and cooperativeness (Roccas *et al.*, 2002). People with high agreeableness levels may favor AI technologies that promote collaborative work and enhance team dynamics, valuing user-friendly and supportive AI interactions that foster a sense of community and mutual respect.

Neuroticism refers to the tendency to experience negative emotions, such as anxiety, anger or depression (Roccas *et al.*, 2002). Individuals with high neuroticism might display more cautiousness or skepticism about AI. They might prefer interfaces that offer clear guidance, reassurance and stress-free navigation to mitigate their concerns and enhance their confidence in using AI tools.

In this study, we investigated whether and how the big five personality traits influence individuals' interactions with AI chatbots in the workplace, especially at the early stages of AI adoption. Specifically, we examined if personality traits affected user engagement with AI, including preferences for specific types of AI chatbot functionalities, perceived ease of use, satisfaction and the potential for creative and efficient task completion. By understanding these dynamics, we aimed to provide insights into designing AI interfaces and systems that are more closely aligned with the diverse psychological profiles of users, thereby enhancing the effectiveness and user experience of AI in professional settings.

Methodology

The methodology design aimed to yield an in-depth understanding of the influence of individual personality traits on user interactions with AI chatbots. We explored the issue through a structured framework involving participant engagement, variable measurement, task execution and metric evaluation.

Participants: We collected data in early 2023, shortly after ChatGPT by OpenAI became available to users. The research engaged a total of 62 participants, randomly divided into two groups, Group A (AI-assisted) and Group B (not AI-assisted), comprising 29 and 33 individuals, respectively. The age distribution of the participants was 18–24 (32%), 25–34 (21%), 35–44 (32%) and 45–54 (15%). Noteworthy, 60% identified as male, 39% as female and 1% as other. The majority of participants (65%) worked full time and 32% pursued a graduate degree. The sample also included 16% of participants who were pursuing executive MBA studies. The remaining part of the participants was in the last year of undergraduate studies in management.

Software: The big five personality traits lied at the heart of our investigation (Costa & McCrae, 1992). We chose these specific traits because of their potential relevance and impact in the context of technology interaction. We quantitatively measured these traits using the Happimeter online platform. Happimeter is a product by the Center for Collective Intelligence at MIT. It aims at quantifying and enhancing individual happiness. The online platform consists of a battery of psychological tests, including the big five. It tracks the mood and offers nuanced, personalized insights into mood dynamics (Gloor, Colladon, Grippa, Budner, & Eirich, 2018; Gloor, Araño, & Guerrazzi, 2020; Sun & Gloor, 2020; Roessler & Gloor, 2021).

Tasks and metrics: We designed the tasks so that they simulated a real-world scenario of using chatbot-based assistants in the workplace. We asked the participants to fill the role of a marketing manager preparing for the launch of a new campaign. We collected data and analyzed it to assess the relationship between the big five personality traits and task quality metrics.

We specifically designed a series of tasks to emulate various facets of user interaction with chatbots. The tasks revolved around creating parts of a marketing campaign for a product, specifically creating a product name, a persona, a competitive analysis and a text-based ad. The following metrics were evaluated in this study:

(1) Quality of tasks: We evaluated the effectiveness of task completion against a set of predefined criteria, which allowed for an objective assessment of the chatbot's utility in facilitating task execution.

(2) Intention to use technology in the future: We assessed the likelihood of future engagement with chatbots through post-task questionnaires. We used this metric with the understanding of the long-term adoption potential of chatbot technologies among users.

Three independent judges evaluated the quality of the output for each task by rating the participants' responses for the tasks on a scale from 1 to 5 on multiple scales. We recruited the judges from academic institutions and companies in Poland and the USA. In the product name task, judges rated the name's originality, its shortness and simplicity, and resonance with the product features, revealing the benefits of the product. For the competitive analysis task, the judges rated the analysis depth and variety, such as the presence of direct and indirect competitors, and substitute products. For the persona task, judges assessed the level of detail in the persona description, the fit of the persona to the product, and the potential of the persona to be used in communication activities. In the text-based ad task, judges assessed the fit to persona and the ability to draw attention. We used these four assessments as a measure of the quality of each task (Appendix A). We calculated Cronbach's alpha to measure the assessment's reliability: the quality of the product name was 0.83, the competitive analysis – 0.98, the text-based ad – 0.96, and the persona – 0.98. The average inter-judge reliability was 0.464 (Krippendorff Alpha) which indicated a moderate level of agreement among the judges.

Statistical analysis

We performed the initial preparation and dataset cleaning using Python standard libraries such as *pandas*, *numpy*, *scipy* and *datetime*. Next, we conducted a statistical analysis using RStudio version 2023.12.1 (RStudio Team, 2021) and *car* library (Fox & Weisberg, 2018). We conducted a two-way analysis of variance to explore the effect of big five traits and interaction with the chatbot on the participants' performance. We used *lsr* library and eta squared function to calculate the effect size (η^2) and partial effect size (η_p^2). We interpreted effect sizes based on established guidelines: η_p^2 around 0.01 – small, η_p^2 around 0.06 – medium, η_p^2 around 0.14 and higher – large (Miles & Shevlin, 2001; Cohen, 2013).

The *post hoc* analyses included simple slopes and pairwise comparisons performed using *interactions* and *emmeans* libraries to investigate specific group differences. In cases when interaction with the group was insignificant, we conducted linear regression analysis using the ordinary least squares (OLS) method to predict performance based on traits. Moreover, we also used such libraries as *dplyr* and *ggplot2* to explore and visualize data. Out of 62 participants, Group A (AI-assisted, $n = 29$) and Group B (not AI-assisted, $n = 33$), we excluded 18 missing cases for the intention to use technology in the future. Thus, we ensured the integrity and validity of the data analysis.

Descriptive statistics: The sample included participants with varying levels of personality traits which allowed the investigation of multiple personality profiles in the interaction with technology (Table 1).

We did not notice significant differences between the means of the groups except for Neuroticism, which was significantly higher in the AI-assisted group ($M = 0.58$, SD = 0.1) compared to the non-AI-assisted group ($M = 0.52$, SD = 0.1) (t (60) = 2.18, $p = 0.03$) (See Table 2).

Spearman's correlation analysis revealed a significant positive relationship between the measures of output quality across all tasks (See Figure 1). We found the strongest relationship between text-based ad and persona tasks ($\rho = 0.84$, $p < 0.001$) as well as text-based ad and

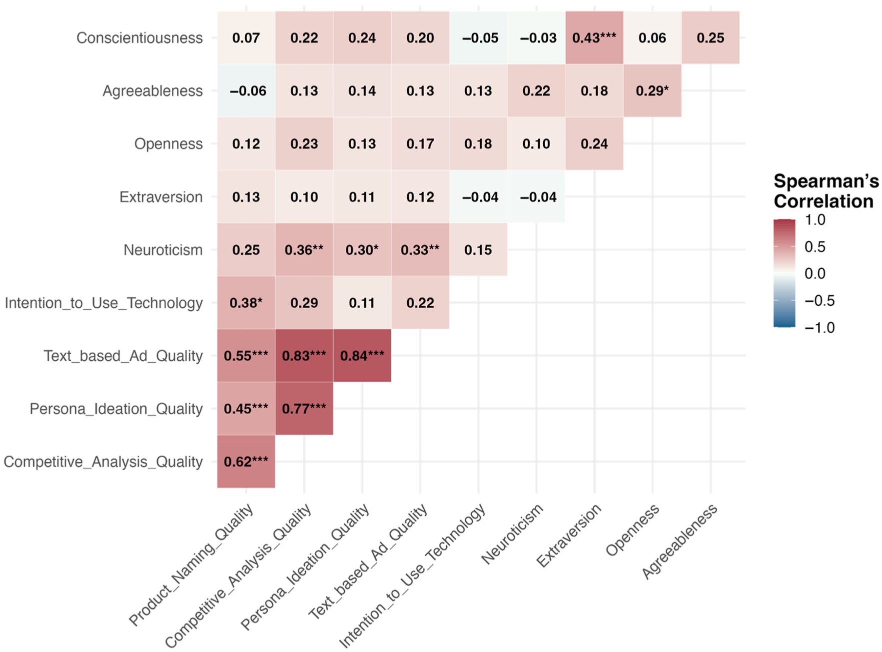
Table 1. Descriptive statistics for personality traits

Descriptive statistics	Agreeableness	Neuroticism	Openness	Extraversion	Conscientiousness
Mean	0.652	0.549	0.623	0.684	0.671
SD	0.086	0.104	0.062	0.072	0.063
Min	0.483	0.283	0.483	0.500	0.517
25%	0.588	0.483	0.583	0.633	0.633
50%	0.650	0.542	0.617	0.683	0.683
75%	0.717	0.617	0.650	0.733	0.713
Max	0.867	0.733	0.783	0.817	0.817

Source: Authors' own elaboration

Table 2. Descriptive statistics and student *t*-test results for traits in AI-assisted vs not AI-assisted groups

Trait	Group	AI-assisted	Not AI-assisted
Neuroticism	Mean	0.58	0.52
	SD	0.10	0.10
	T-test	t (60) = 2.18, *p* = 0.03	
Extraversion	Mean	0.69	0.68
	SD	0.08	0.07
	T-test	t (60) = 0.76, *p* = 0.45	
Openness	Mean	0.63	0.62
	SD	0.06	0.06
	T-test	t (60) = 0.87, *p* = 0.39	
Agreeableness	Mean	0.67	0.64
	SD	0.08	0.09
	T-test	t (60) = 1.45, *p* = 0.15	
Conscientiousness	Mean	0.68	0.67
	SD	0.06	0.07
	T-test	t (60) = 0.57, *p* = 0.57	



Note(s): *: p value < 0.05, **: p value < 0.01, ***: p value < 0.001
Source(s): Authors' own elaboration

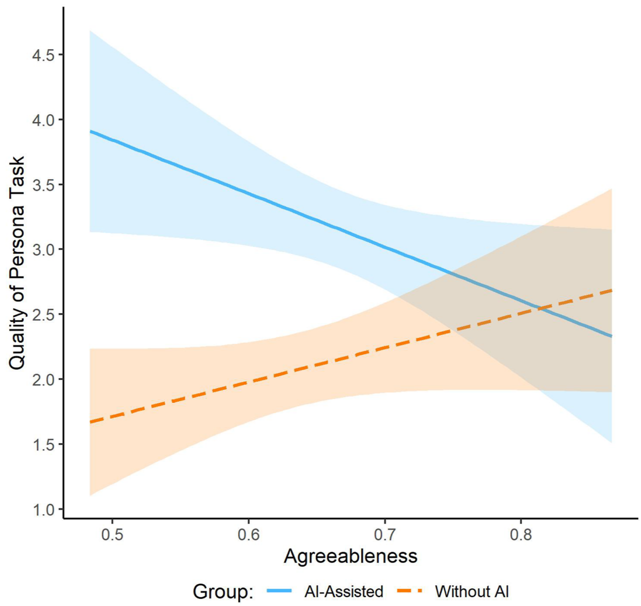
Figure 1. Correlation between the variables

competitive analysis tasks ($\rho = 0.83$, $p < 0.001$). The intention to use technology was significantly positively correlated with the quality of the product naming task ($\rho = 0.38$, $p = 0.01$). Moreover, we found a significant positive relationship between neuroticism and the quality of all tasks, except for the product naming task, indicating that individuals with higher levels of neuroticism performed better across most tasks. The analysis also identified correlations between extraversion and conscientiousness ($\rho = 0.43$, $p < 0.001$), as well as openness and agreeableness ($\rho = 0.29$, $p = 0.01$).

In the next section, we will compare participants with different levels of personality traits (minimum, average and maximum) in the AI-assisted and not AI-assisted groups.

Agreeableness: We examined the interaction between individual differences in agreeableness and group in predicting the quality of the tasks. We identified a significant interaction effect specifically for the quality of persona building task (F (1, 58) = 7.325, $p = 0.0089$, $\eta_p^2 = 0.11$). This indicates that the effect of agreeableness on the quality of the persona task varied depending on whether participants interacted with the chatbot or not. The effect size was medium. Simple slopes analysis revealed that the relationship between agreeableness and the quality of the persona task in the group with the chatbot was statistically significant and negative (estimate = −4.13, t (58) = −2.14, $p = 0.04$) (See Figure 2). Conversely, the relationship between agreeableness and the quality of the persona task in the group without the chatbot was not statistically significant.

We conducted pairwise comparisons to further investigate the interaction between the agreeableness trait and group (AI-assisted vs not AI-assisted) in predicting the quality of tasks. The results revealed that less agreeable individuals (at the minimum level of the trait) tended to produce higher quality of persona task when interacting with the chatbot (estimated marginal mean (EMM) = 3.91, SE = 0.388) compared to the group without the chatbot's help (EMM = 1.67, SE = 0.283) (t(58) = 4.671, $p = 0.0003$) (See Table 3). We observed a similar effect for individuals with a moderate level of agreeableness (at the level of mean) (t(58) = 5.221, $p < 0.0001$). However, the effect was insignificant for very agreeable individuals classified (at the maximum level of trait) ($p > 0.05$). These findings suggest that the chatbot's presence had a differential impact on task quality based on individuals' agreeableness levels.



Note(s): Bands represent 95% confidence intervals
Source(s): Authors' own elaboration

Figure 2. Simple slopes for the quality of persona task for agreeableness and groups

Table 3. Pairwise comparisons for the quality of persona task for agreeableness and groups

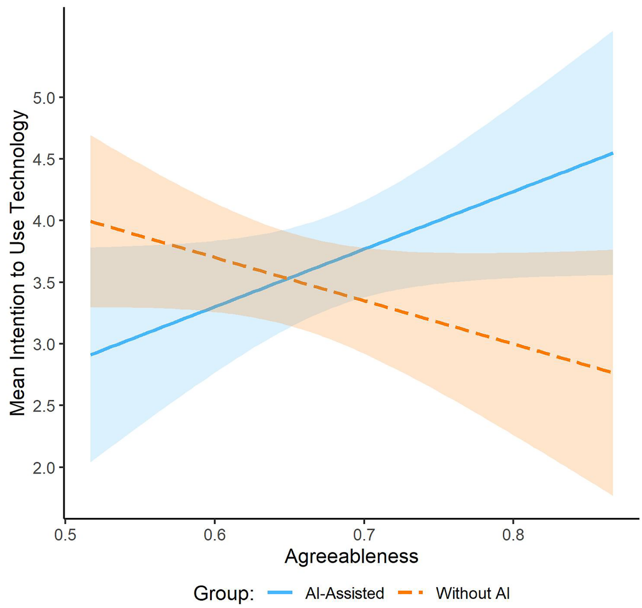
Group	Agreeableness	EMM	SE	Estimate	SE	df	*t*
AI-assisted	Low	3.91	0.388	2.242	0.48	58	4.67***
Not AI-assisted	Low	1.67	0.283				
AI-assisted	Moderate	3.22	0.155	1.1	0.211	58	5.22***
Not AI-assisted	Moderate	2.11	0.144				
AI-assisted	High	2.33	0.411	−0.357	0.57	58	−0.627
Not AI-assisted	High	2.68	0.393				

Source(s): Authors' own elaboration

Next, we explored the effect of agreeableness and group on the intention to use technology in the future. Our analysis revealed a significant interaction of agreeableness with the group in predicting the intention to use technology in future (F (1, 40) = 6.478, $p = 0.015$, $\eta_p^2 = 0.14$). The effect size was large. Simple slopes analysis was significant on the level of trend only for the group interacting with the chatbot (estimate = 4.68, t (40) = 1.95, $p = 0.06$) and implied a possible positive relationship between the intention to use technology in future and agreeableness in this group (Figure 3).

We noted the highest intention to use in the group of agreeable participants interacting with the chatbot (EMM = 4.55, SE = 0.49). There were significant differences compared to the non-AI-assisted group (EMM = 2.76, SE = 0.49) (estimate = 1.79, t (40) = 2.564, $p = 0.014$) (See Table 4).

We observed a reverse effect for the low level of agreeableness. Participants who did not use chatbot help had a higher intention to use technology (EMM = 4.11, SE = 0.41)



Note(s): Bands represent 95% confidence intervals

Source(s): Authors' own elaboration

Figure 3. Simple slopes for the intention to use technology for agreeableness and groups

Table 4. Pairwise comparisons for the intention to use technology for agreeableness and groups

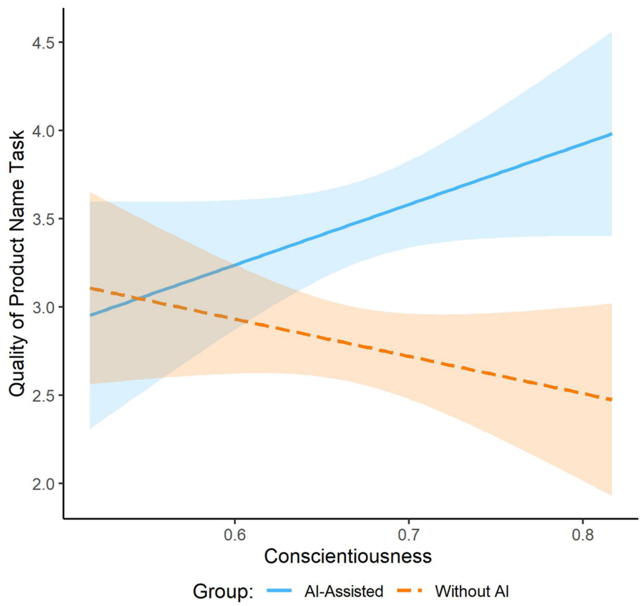
Group	Agreeableness	EMM	SE	Estimate	SE	Df	*t*
AI-Assisted	Low	2.71	0.505	−1.36	0.649	40	−2.09*
Not AI-assisted	Low	4.11	0.409				
AI-Assisted	Moderate	3.54	0.197	0.0261	0.272	40	0.096
Not AI-assisted	Moderate	3.52	0.187				
AI-Assisted	High	4.55	0.491	1.79	0.697	40	2.564*
Not AI-assisted	High	2.76	0.494				

Source(s): Authors' own elaboration

compared to the ones who conducted the task with the chatbot (EMM = 2.71, SE = 0.51) (t (40) = −2.09, p = 0.043).

Conscientiousness: We examined the interaction between individual differences in conscientiousness and group in predicting the quality of the tasks. The findings revealed a significant interaction between conscientiousness and group specifically in the prediction of the quality of product name task ($F(1, 58) = 4.8343$, $p = 0.032$, $\eta_p^2 = 0.08$). The effect size was medium. Simple slope analysis was positive and significant on the level of trend only for the group interacting with the chatbot (estimate = 3.43, t = 1.82, p = 0.07) (See Figure 4). This implies that higher conscientiousness can potentially relate to better performance but only in the AI-assisted group.

Pairwise comparisons revealed significant effects for the moderately (at the mean level of the trait) and highly (at the maximum level of the trait) conscientious individuals and no difference for the low level (at the minimum level) of the trait. Individuals with high



Note(s): Bands represent 95% confidence intervals
Source(s): Authors' own elaboration

Figure 4. Simple slopes for the quality of product name task for conscientiousness and groups

conscientiousness tended to produce higher quality of product name tasks when interacting with the chatbot (EMM = 3.91, SE = 0.388) compared to the group without the chatbot (EMM = 2.47, SE = 0.273) ($t(58) = 3.79$, $p = 0.0004$) (See Table 5). We observed a similar effect for individuals with a moderate level of conscientiousness ($t(58) = 4.812$, $p < 0.0001$).

We found no significant effects of individual differences in conscientiousness and group on intention to use technology in future (See Figure 8 in Appendix B).

Neuroticism: There was no interaction with group and neuroticism in the prediction of quality of tasks. However, individual differences in Neuroticism significantly predicted quality of persona ($F(1,60) = 5.618$, $p = 0.021$, $\eta^2 = 0.09$), Facebook ad ($F(1,60) = 9.48$, $p = 0.03$, $\eta^2 = 0.05$) and competitors ($F(1,60) = 10.4$, $p = 0.02$, $\eta^2 = 0.14$) tasks. Neuroticism trait predicted results of product name task only on the level of trend ($F(1,60) = 3.36$, $p = 0.07$). More neurotic participants had better quality of persona task ($\beta = 2.815$, SE = 1.18), Facebook ad ($\beta = 3.24$, SE = 1.05) and competitors ($\beta = 4.04$, SE = 1.25) tasks (See Figure 5).

We found no significant interaction effect of neuroticism and group in prediction of intention to use technology in the future (See Figure 9 in Appendix B).

Openness and extraversion: We found no significant effects of individual differences in openness and extraversion and group on the quality of task or intention to use technology in future (See Figures 6–13 in Appendix B).

For a detailed summary of the results, see Table 7 in Appendix C.

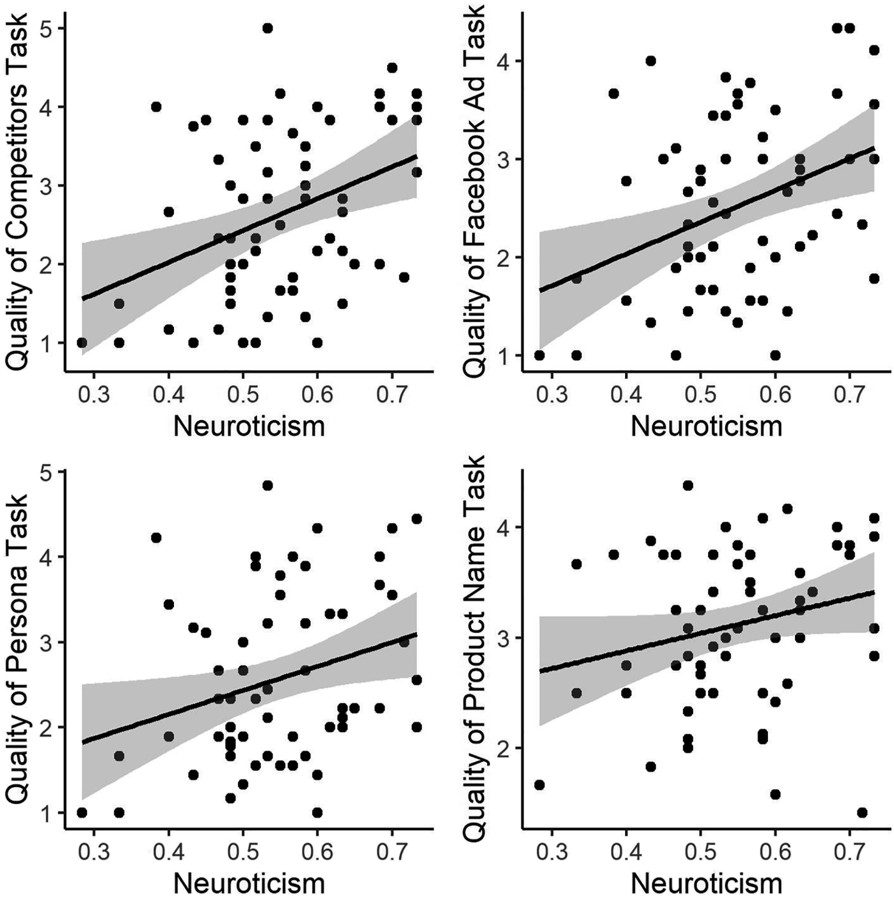
Discussion

Our study focused on the effect of personality on AI adoption attempting to fill the gap in AI research particularly during the phase of early adoption. We conducted this pilot study in early 2023, shortly after ChatGPT by OpenAI became available to users. Therefore, this study evaluated the attitudes of early adopters when technologies like ChatGPT were not yet widely used. Consequently, the study provides insights into how individuals interacted with AI chatbots at a time when they were still relatively new and unfamiliar.

At these early stages, our results suggest that personality traits influence human–AI interaction. Particularly agreeableness and conscientiousness interact with task quality when using AI chatbots. The observed effects were medium and large. This indicates a substantial relationship between these traits and the outcomes. We linked higher levels of conscientiousness to enhanced task performance, particularly in AI-assisted settings, aligning with previous research in human–computer interaction (HCI) literature (Cruz-Maya & Tapus, 2016). Conversely, less agreeable individuals demonstrated higher task quality when assisted by AI technology compared to the non-AI-assisted group. Individuals low in agreeableness often exhibit tendencies such as assertiveness and independence (Kammrath, McCarthy, Cortes, & Friesen, 2015), thus, when provided with AI assistance, these individuals may thrive, leveraging the autonomy, objectivity and efficiency provided by AI technology to overcome challenges typically associated with teamwork. Furthermore, our investigation unveiled a significant interaction between agreeableness and technology engagement in predicting individuals' future technology adoption intentions. Agreeable participants

Table 5. Pairwise comparisons for the quality of product name task for conscientiousness and groups

Group	Conscientiousness	EMM	SE	Estimate	SE	Df	*t*
AI-assisted	Low	2.95	0.321	−0.153	0.421	58	−0.364
Not AI-assisted	Low	3.11	0.272				
AI-assisted	Moderate	3.52	0.115	0.767	0.159	58	4.812***
Not AI-assisted	Moderate	2.76	0.11				
AI-assisted	High	3.98	0.29	1.51	0.398	58	3.791***
Not AI-assisted	High	2.47	0.273				



Note(s): Bands represent 95% confidence intervals
Source(s): Authors' own elaboration

Figure 5. Relationship between quality of tasks and neuroticism

displayed a stronger inclination toward technology adoption, especially in the presence of AI assistance, consistent with recent findings (Stein, Messingschlager, Gnambs, Hutmacher, & Appel, 2024). This underscores the influential role of personality traits in shaping attitudes toward technological advancements. Neuroticism emerged as a determinant of quality across various tasks, regardless of chatbot usage. Contrary to conventional beliefs that associate neuroticism with unfavorable workplace outcomes, our findings suggest a different perspective. Similarly to Beckmann, Birney, Minbashian, and Beckmann (2021), we found that moderate levels of neuroticism can benefit cognitive task performance.

While we observed no significant effects for openness and extraversion and task quality or intention to use technology, their roles warrant further exploration in future studies. Understanding the influence of personality traits on chatbot interaction can guide designers in creating more personalized and effective systems.

Understanding the effect of personality in early adoption stages helped us formulate suggestions for designing and implementing chatbot and other generative AI-powered technologies. Based on our findings, generative AI-powered technologies should consider personality traits as important factors. For example, agreeable users may be more likely to interact with chatbots that are friendly and approachable, while conscientious users may be more likely to interact with chatbots that are accurate and reliable. By taking it into account, chatbots and generative AI systems can be designed to be more effective and user-friendly, which can lead to improved task performance and user satisfaction.

Implications for research and practice

The findings of this pilot study extend our understanding of user interaction with generative AI technologies, particularly from the point of view of the user's personality traits. This research highlights how personality traits influence user engagement with generative AI, providing a basis for developing more personalized and effective AI-based systems. For researchers, this model opens new avenues for exploring the psychological dimensions of AI adoption and its impact on productivity and user satisfaction. Practitioners can leverage these insights to design AI tools that cater to diverse user profiles, thereby enhancing the efficiency and satisfaction of AI-assisted tasks. Societally, the study underscores the importance of integrating psychological principles into AI development. This promotes a more human-centric approach to technology adoption, leading to greater acceptance and optimal utilization of AI innovations.

Limitations and future research

While this study offers new understanding of the relationship between personality traits and interactions with generative AI, we must address certain limitations. One limitation was the relatively small sample size of 62 participants. This limitation raises concerns about the sample's representativeness, as it may not capture the full spectrum of personality diversity of a broader population. For example, the effect of neuroticism on performance could have happened due to the higher levels of neuroticism in the AI-assisted group, which occurred by chance despite the random assignment of participants. Future research directions should consider expanding the participant base to include a larger and more diverse group.

Conclusions

The pilot study investigated the impact of personality traits on user engagement with chatbots. Drawing on the big five personality traits framework, we explored how individual differences in openness, conscientiousness, extraversion, agreeableness and neuroticism influence the way people interact with AI chatbots. The findings indicated that personality traits play a significant role in shaping users' interactions. This study contributes to the growing body of literature on human–AI interaction and has implications for designing and developing more effective and user-friendly AI applications. The findings suggest that tailoring AI technologies to better fit the users' psychological profiles can enhance user engagement and improve task performance.

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Supplementary material
The supplementary material for this article can be found online.

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