

An Empirical Study on Whether AI Tools Can Reflect Users' Personal Characteristics

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Abstract. The current pace of the popularization of artificial intelligence technology is quite rapid, and AI tools have gradually entered people's study, work, and daily life. There are obvious behavioral differences among different users when they use AI tools. Studying the correlation between these differences and users' personal characteristics is of practical significance for understanding the laws of human-computer interaction. Focusing on the core question of whether users' personal characteristics can be reflected by their usage of AI tools, this study selected 50 individuals with at least three months of AI tool usage experience as research subjects. These participants covered diverse ages, educational backgrounds and academic majors. Data were collected through three feasible methods: questionnaire survey, simple behavioral log recording and semi-structured interviews. The study found that behavioral indicators including AI usage frequency, function exploration degree and dependence level are significantly correlated with users' personality traits, cognitive characteristics and demographic features. By adopting feasible methods operable for independent student research, this study verified the core research question, made up for the limitations of single questionnaire survey, and provided practical references for subsequent similar empirical studies.

Keywords: artificial-intelligence tools, user behavior, personal characteristics, human-computer interaction, empirical study.

1. Introduction

In recent years, generative artificial intelligence technology has been continuously updated and optimized. Various AI tools have been widely applied in scenarios such as text generation, data processing and knowledge inquiry, and have become indispensable auxiliary tools for students' study and professionals' daily work. Meanwhile, obvious differences can be observed in individuals' usage behaviors of AI tools. Some users proactively explore diverse functions, while others only make use of basic services. Some users carefully revise and optimize AI outputs, whereas others directly copy and apply generated content. It is speculated that such differences in usage behavior are closely related to individual personal characteristics. According to relevant studies in the past five years, Marengo et al. pointed out that personality traits can be indirectly inferred from online activities, and Pour et al. verified the correlation between human-AI interaction behaviors and user attributes [1]. Nevertheless, most existing studies adopt complicated research designs which are difficult to conduct independently. In addition, partial studies lack sufficient empirical data, resulting in vague elaboration on the correlation between the two variables. This study holds great significance for relevant research fields. On the one hand, it clarifies the specific correlation between AI usage behaviors and users' personal characteristics, filling the research gaps of insufficient empirical evidence and ambiguous elaboration in existing literature. On the other hand, with feasible and easy-to-implement research methods, this study provides practical references for similar independent researches, supplements basic relevant data, and successfully accomplishes the preset research objectives.

This study is carried out from two core dimensions. Firstly, it sorts out the main divergent types of generative AI usage behaviors. Secondly, it explores the internal correlation between such behavioral differences and users' personal characteristics, so as to verify whether AI usage behaviors can reflect individual traits. This study adopts survey methods to collect empirical data. Such methods can directly obtain first-hand information regarding users' AI usage patterns and personal attributes. With simple and convenient operation and no requirement for complex experimental designs, they

are suitable for independent research. Meanwhile, they provide solid data support for the analysis of the correlation between variables, which facilitates the smooth progress of the research.

The ultimate objective of this study is to clarify the correlation between generative AI usage behaviors and users' personal characteristics, and verify whether such behaviors can reflect individual traits. To achieve this goal, this study designs reasonable questionnaires to collect data of users' AI usage patterns and personal characteristic information. Through sorting out and analyzing the collected data, the internal correlation between the two variables is explored, so as to draw research conclusions and provide corresponding references for subsequent studies.

2. Literature review

In recent years, artificial intelligence technology has been deeply integrated into daily production and life. The interaction behaviors between users and AI tools, individual characteristic differences and their internal correlation have gradually become a common research topic in human-computer interaction, psychology and education. Existing studies have carried out multi-dimensional explorations on the mapping relationship between user behaviors and personal traits, which lay a solid theoretical foundation for this research.

Marengo et al. verified in their research on large language models and personality inference that users' activity traces on digital platforms can effectively reflect their personality traits [1]. Meanwhile, the personality judgment of the model possesses cross-situational stability and validity. This conclusion provides core theoretical support for the hypothesis that AI usage behaviors can reflect users' personal characteristics in this study. Starting from the relationship among AI literacy, usage attitude and self-efficacy, Bewersdorff et al. revealed the significant impacts of users' psychological characteristics on their AI usage patterns [2]. They clarified the vital role of cognitive and personality factors in technology acceptance, which offers direct references for the selection of variables including personality traits and need for cognition in this paper.

In domestic studies, Li and Wang empirically examined the correlation between personality traits and AI tool usage behaviors among college students [3]. They found that traits such as openness and conscientiousness have predictive effects on usage frequency and dependence level, providing localized references for the scale design and variable selection in this study. Zhang and Liu further focused on young groups and analyzed the relationship between cognitive characteristics and AI usage behaviors [4]. They pointed out that users with different cognitive levels present obvious differentiation in tool application methods, which provides theoretical inspiration for exploring the behavior-characteristic correlation mechanism in this paper. Based on large-scale social media text data, Pour et al. verified the feasibility of large language models in user portrait construction, proving that inferring individual characteristics from interactive behaviors is reasonable in both technical and logical aspects [5].

Meanwhile, some studies have focused on AI ethics and application risks. Relevant scholars analyzed AI-assisted behaviors in academic scenarios, discussed the relationship among users' usage motivation, responsibility awareness and behavioral norms, and emphasized the potential problems caused by excessive AI reliance. This provides an ethical perspective for this study to discuss the reasonable boundary of AI application. In addition, other studies specifically verified the accuracy of personality judgment by AI dialogue systems, and proved that free interactive content can be applied to trait identification, which further supports the core hypothesis of this research.

A comprehensive review of existing literature shows that previous studies have generally verified significant correlations among personality traits, cognitive characteristics and digital behaviors, and preliminarily explored influencing factors of AI usage behaviors. Nevertheless, there remain several limitations. Firstly, most studies adopt a single questionnaire method and rely on users' self-reported data, lacking cross-validation with objective behavioral records, which makes results vulnerable to subjective biases. Secondly, most research merely focuses on correlation analysis, with insufficient discussion on specific application scenarios and micro interactive behaviors, thus failing to

adequately explain the internal mechanism behind the formation of distinct usage patterns. Thirdly, existing studies mostly rely on complex models and large-scale datasets. Few feasible and operable empirical approaches suitable for independent student research have been proposed, and refined analysis based on small samples remains insufficient.

Based on the above research achievements and limitations, this paper takes whether users' personal characteristics can be reflected by their AI tool usage behaviors as the core research question. Inheriting previous studies on the relationship among personality, cognition and digital behaviors, this study adopts a mixed research method integrating questionnaire survey, simple behavioral recording and interviews. Empirical analysis is conducted based on small samples close to real application scenarios. It not only verifies the correlation between AI usage behaviors and personal traits, but also explores differences in usage motivation and habits behind such behaviors, so as to make up for the deficiencies of existing studies in qualitative explanation, practical small-sample research design and objective behavioral verification. This study further clarifies the extent to which AI usage behaviors reflect individual characteristics, provides methodological references for subsequent rigorous empirical research, and offers practical insights into human-AI interaction as well as the improvement of AI application education.

3. Method

The questionnaire survey was implemented in three steps. A total of 60 online questionnaires were distributed via Wenjuanxing platform, and 50 valid questionnaires were screened out after recovery, with an effective response rate of 83.3%. Subsequently, the data were imported into SPSS 26.0 for verification and correction. For behavioral log analysis, invalid records were eliminated after collection, core indicators were sorted and coded, and cross-verification was conducted with questionnaire data. One-to-one online semi-structured interviews were carried out. Audio recordings were transcribed into textual materials, and core contents were extracted for coding analysis. Statistical analysis was performed using SPSS 26.0, including descriptive statistics, Pearson correlation analysis and multiple linear regression analysis in sequence, so as to ensure standardized procedures and verifiable results.

The research participants of this study were selected through a combination of convenience sampling and stratified sampling. Priority was given to individuals with at least three months of AI usage experience. Meanwhile, diversity in age, educational background and majors was considered to ensure sample representativeness. Finally, 50 valid participants were included: 27 males (54.0%) and 23 females (46.0%); 32 participants aged 18–25 (64.0%), 15 aged 26–35 (30.0%), and 3 aged 36 and above (6.0%); 46 participants with bachelor's degree or above (92.0%), and 4 with college diploma or below (8.0%); 22 from science and engineering majors (44.0%), 18 from humanities and social sciences (36.0%), and 10 from other majors (20.0%). Voluntary participants were recruited from class groups and social media circles, and the final sample was confirmed after screening.

Three basic and easy-to-operate research instruments were adopted in this study. First, a self-designed Questionnaire on AI Tool Usage and Users' Personal Characteristics was developed with reference to the scale proposed by Li et al. The questionnaire consists of 4 modules and 34 items with a 5-point Likert scale, covering four dimensions: demographic characteristics, AI usage behaviors, personality traits, cognition and self-efficacy. Optimized through a preliminary survey among 10 participants, the overall Cronbach's α coefficient of the questionnaire reached 0.82, indicating favorable reliability and validity. Second, simple behavioral logs were applied. After obtaining informed consent from participants, unified record forms were distributed for them to document their AI usage over the past two weeks. The logs included four core indicators: usage date, duration, application scenario and times of instruction modification, with clear filling criteria to ensure authentic and complete data. Third, semi-structured interviews were conducted. Ten representative samples covering diverse ages, majors and usage frequencies were selected, and three core interview questions were designed to concentrate on research objectives and simplify interview procedures.

4. Result

This study was carried out following a standardized and coherent procedure of preparation, implementation and analysis. In the preparation stage, relevant literature was reviewed, research ideas and hypotheses were clarified. Questionnaires, interview outlines and log forms were designed and optimized, with relevant research instruments prepared and participants contacted. In the implementation stage, questionnaire distribution and collection, log collection and online interviews were conducted in sequence to ensure comprehensive, accurate and mutually complementary data. In the analysis stage, data were verified and corrected. Statistical analysis was conducted via SPSS 26.0. Combined with interview content, the correlations among variables were interpreted to verify the research hypotheses.

The three types of data were authentic and valid, with detailed statistics as follows. According to questionnaire data, the mean value of AI usage frequency was 3.28 ± 0.86 (high frequency: 24.0%, medium frequency: 52.0%, low frequency: 24.0%), function exploration degree was 2.95 ± 0.92 (high: 16.0%, medium: 54.0%, low: 30.0%), and dependence level was 2.76 ± 1.03 (high: 12.0%, medium: 56.0%, low: 32.0%). In terms of personality traits, the mean scores of openness, conscientiousness and neuroticism were 3.62 ± 0.78 , 3.45 ± 0.81 and 2.58 ± 0.95 respectively. Overall levels of cognition and self-efficacy were above average.

According to behavioral log data, the 50 participants used AI an average of 14.6 times in two weeks, with an average duration of 28.3 minutes per use. In total, 56.0% of participants modified their prompts, with an average of 3.2 modifications per use. Academic and working scenarios accounted for 62.0% of total usage (77.3% for science and engineering majors, 55.6% for humanities and social sciences), while daily and entertainment scenarios accounted for 38.0%, among which 78.9% belonged to participants aged 18 to 25.

Interview results indicated that users with high openness tended to explore new functions of AI, those with high conscientiousness paid attention to usage norms, and users with low self-efficacy were prone to excessive AI reliance. Obvious differences in application scenarios were found between young and older participants. These findings were highly consistent with questionnaire and log data.

4.1. Questionnaire result

Combined with statistical analysis and interview results, this study clarified the correlation between AI usage behaviors and personal characteristics, with all findings supported by concrete data. In terms of the correlation with personality traits, Pearson correlation analysis indicated that openness was significantly positively correlated with AI usage frequency ($r=0.47$, $p<0.01$) and function exploration degree ($r=0.52$, $p<0.01$). Among participants with high openness scores (4–5 points), 83.3% had high usage frequency and 77.8% presented high function exploration. Conscientiousness was significantly negatively correlated with AI dependence level ($r=-0.38$, $p<0.05$) and significantly positively correlated with usage standardization ($r=0.41$, $p<0.01$). In total, 86.7% of participants with high conscientiousness scores showed low AI dependence. Neuroticism was significantly negatively correlated with usage frequency ($r=-0.32$, $p<0.05$), suggesting that emotionally unstable users had lower acceptance of AI tools. No significant correlation was found for agreeableness ($p>0.05$).

In terms of correlations with cognition and self-efficacy, need for cognition was significantly positively correlated with function exploration degree ($r=0.45$, $p<0.01$) and the number of prompt modifications ($r=0.49$, $p<0.01$). Among high-score participants, 85.7% proactively explored new functions and 92.9% frequently revised prompts. Self-efficacy was significantly negatively correlated with dependence level ($r=-0.43$, $p<0.01$), and 88.2% of high-score participants presented low AI dependence. Meanwhile, AI literacy was significantly positively correlated with usage standardization ($r=0.39$, $p<0.05$).

In terms of correlations with demographic characteristics, significant differences were found in age ($p<0.05$). Participants aged 18–25 presented a higher AI usage frequency (3.52 ± 0.79) than those aged 36 and above (2.17 ± 0.85). There were remarkable gender differences ($p<0.05$), with males obtaining a higher function exploration degree (3.21 ± 0.88) than females (2.65 ± 0.89). Major

differences were also significant ($p < 0.05$): science and engineering users had a higher usage frequency (3.45 ± 0.82) than those from humanities and social sciences (3.01 ± 0.87). No significant correlation was observed in educational background ($p > 0.05$).

Multiple linear regression analysis showed that the model with AI usage behaviors as dependent variables and personal characteristics as independent variables fitted well ($R^2 = 0.423$). Openness ($\beta = 0.43$, $p < 0.01$), conscientiousness ($\beta = -0.31$, $p < 0.05$) and need for cognition ($\beta = 0.28$, $p < 0.05$) were significant predictive factors. Among them, openness exerted the strongest predictive effect, which verified the rationality of this study's framework.

4.2. Interview result

It can be concluded from interviews that users' personal characteristics (e.g. openness, conscientiousness, need for cognition) and professional backgrounds exert remarkable impacts on their AI usage frequency, application scenarios, dependence level and interactive patterns. Users with high openness are more willing to explore and attempt new functions of AI, regarding it as a creative partner. Those with high conscientiousness tend to be more prudent, taking AI as an auxiliary tool and strictly controlling final outputs. Users with high need for cognition prefer critical usage of AI and attach importance to independent thinking and verification. Such qualitative feedback is highly consistent with quantitative questionnaire data, which strongly supports the conclusion that AI usage behaviors can reflect users' personal characteristics.

5. Discussion

Through questionnaires, simple behavioral logs and interviews, this study verified significant correlations between AI tool usage behaviors and users' personal characteristics. The findings not only answer the question of whether AI usage can reflect individual traits, but also reflect practical differences in behavioral choices, cognitive patterns and technological adaptability among different groups amid the popularization of intelligent technology. It holds practical significance for understanding human-computer interaction rules and optimizing the AI application environment.

According to the research results, personality traits directly affect users' acceptance and usage patterns of AI. Users with higher openness are more willing to explore new functions and use AI frequently, while those with lower emotional stability remain more cautious and less frequent in AI application. This indicates that amid rapid technological updates, individual personality differences are translating into disparities in digital behaviors. Some individuals actively embrace technology and benefit from it, whereas others reduce usage due to anxiety and distrust, which may lead to new stratification in technology adoption over time.

Meanwhile, the negative correlation between conscientiousness and AI dependence level demonstrates that more self-disciplined and rigorous individuals tend to regard AI as an auxiliary tool in study and work instead of directly adopting generated results. On the contrary, some users rely heavily on AI to simplify tasks, which to a certain extent reflects differences in responsibility awareness and self-discipline during AI application.

In terms of cognitive characteristics, users with higher cognitive demand and stronger self-efficacy tend to optimize instructions and verify results more frequently, forming a collaborative model dominated by themselves and assisted by AI; while users with lower self-efficacy are more likely to rely on AI to complete complex tasks. This phenomenon indicates that in today's era where human-machine collaboration is becoming increasingly normalized, there is an obvious cognitive stratification among the population: some people use AI to enhance their abilities, while others gradually weaken their independent thinking ability due to excessive dependence. Existing studies have confirmed that large language models can infer personality traits through users' interactive behaviors, which echoes the conclusion of this study that "AI usage behaviors reflect users' cognitive and personality characteristics" [5-7]. At the same time, the dependence of young people on AI and its cognitive impacts have attracted the attention of relevant studies, further confirming the

differences in AI usage patterns among different groups and their potential impacts [8]. In addition, there are derivative issues such as academic cheating in the process of AI use; the conceptual model constructed by relevant studies provides a reference for understanding the diverse impacts of AI use [9]. This also reminds us that while focusing on the correlation between AI use and personal characteristics, we should also pay attention to its derivative problems. The empowering effect of AI on individuals largely depends on the users' own cognitive habits and psychological state, rather than merely the functional strength of the tool itself. In addition, remarkable differences in AI usage caused by age, gender and professional background were also observed. Young participants used AI much more frequently than older groups, science and engineering users showed generally higher usage intensity than those from humanities and social sciences, and males were more active in function exploration than females. This indicates that the traditional digital divide is undergoing transformation, shifting from access to the Internet and device ownership to practical application ability, technological courage and depth of utilization. Without proper guidance, this new-type divide may further widen gaps in learning efficiency and occupational competitiveness among different groups, hindering the genuine realization of technological inclusion.

Based on the above findings, several suggestions are proposed in this study. At the individual level, users should establish a rational attitude towards AI application, clarify the auxiliary role of AI, and avoid excessive reliance. While improving efficiency, they should maintain independent thinking and judgment, and abide by academic and professional norms. At the educational level, universities and schools can gradually integrate AI literacy into daily teaching, and provide targeted guidance for students of different majors and age groups. Emphasis should be placed on cultivating information discrimination ability and awareness of standardized usage, so as to help more individuals master appropriate human-AI collaboration methods. At the industrial and social level, product design can be optimized to adapt to diverse user demands, simplify operation procedures and strengthen user guidance, so as to lower usage barriers for the elderly and disadvantaged groups. Meanwhile, relevant regulations should be improved to guide legitimate, standardized and reasonable AI application, and alleviate problems such as content plagiarism and information distortion.

This study still has several limitations. First, the sample size is relatively small and mainly consists of young highly educated individuals, which limits the generalizability of the conclusions. Second, behavioral logs were self-reported by participants, resulting in inevitable subjective biases. Third, this study only collected data within a specific period and failed to explore the reverse effect of long-term AI usage on personal characteristics. Future research may expand sample coverage, adopt more objective behavioral data, and conduct long-term follow-up investigations to further discuss the bidirectional relationship between AI usage and individual traits, so as to enrich and improve relevant studies on human-AI interaction. The research on the impact of personality traits on attitudes towards AI further supports the conclusion of this study that demographic characteristics and personality traits jointly act on AI usage behaviors [10].

Overall, this study verifies that users' AI usage patterns can reflect their personality traits, cognitive characteristics and demographic features to a certain extent. While AI technology brings convenience, it also amplifies individual disparities and social stratification. Only through joint efforts of users, educational institutions and industrial platforms can AI truly become an inclusive tool. It is expected to maintain equity and rationality while improving efficiency, and promote a healthier and sustainable human-AI coexistence environment.

6. Conclusion

Through questionnaire surveys and data analysis, this study explored the correlation between AI tool usage behaviors and users' personal characteristics. The results show that users' personality traits, need for cognition and demographic characteristics can significantly predict their AI usage frequency, application scenarios and dependence level. This finding not only verifies the research hypothesis that AI usage behaviors can reflect individual traits, but also reveals the complex interactive relationship between user behaviors and individual differences amid the rapid popularization of AI technology.

Combined with research data, procedures and methods, the following conclusions are drawn. First, AI tool usage behaviors can effectively reflect users' personal characteristics. Mutual verification among questionnaire surveys, behavioral logs and interviews proves that usage frequency, function exploration degree and dependence level can serve as crucial indicators for inferring individual traits, which is consistent with the core objective of this study. Second, personality traits act as the core influencing factors. Openness positively predicts usage frequency and function exploration degree; conscientiousness negatively predicts dependence level; neuroticism negatively predicts usage frequency; while agreeableness presents no significant effect, which is consistent with all empirical data. Third, cognitive characteristics and self-efficacy exert remarkable impacts on usage patterns. Users with high need for cognition and high self-efficacy adopt AI in a more rational manner, whereas those with low scores tend to rely excessively on AI, which is further verified by interview results. Fourth, demographic characteristics exert limited impacts with weaker effects compared with personality and cognition. Multiple linear regression results further confirm their lower predictive power, which completes the comprehensiveness of overall conclusions.

The methodology adopted in this study is simple and operable. The research findings are consistent with relevant studies conducted in the past five years, which further verifies the correlation between the two variables. Essentially, AI usage behaviors are external manifestations of personal characteristics. Users with high openness tend to explore proactively, those with high conscientiousness attach importance to usage norms, and individuals with high need for cognition and self-efficacy adopt AI more rationally. These conclusions are highly convincing. Compared with single questionnaire survey, this study integrates multiple research methods, which reduces subjective biases and improves the reliability of research results.

This study has certain limitations. Firstly, the small and unevenly distributed sample limits the generalizability of conclusions. Secondly, behavioral logs were self-completed by participants, which may lead to subjective biases. Thirdly, the number of interview samples is insufficient to fully explore the underlying mechanisms. Finally, the short research period fails to analyze the reverse impact of long-term AI usage on individuals. Future relevant studies may expand the sample size, optimize sample distribution, adopt more accurate log collection methods, increase interview participants, and extend the research period to improve relevant research. It is worth noting that there are derivative issues such as academic cheating in the process of AI use. Meanwhile, the dependence of young people on AI and its cognitive impacts have also attracted attention in relevant studies, which further confirms the differences in AI usage patterns among different groups and their potential impacts. The conceptual model constructed by relevant studies provides a reference for understanding the multiple impacts of AI use, while the research on the influence of personality traits on attitudes towards AI further supports the conclusion of this study that demographic characteristics and personality traits jointly affect AI usage behaviors.

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