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Research Paper

User Satisfaction with AI-Generated Versus Human-Assisted Personality Reports: A Quasi-Experimental Study on Indian College Students

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ABSTRACT

This article explored the integration of AI and personality assessment (based on the BIG-5) in the field of psychology. The purpose of the study was to evaluate user satisfaction between a human-assisted personality report and an AI-generated personality report. This quasi-experimental study was conducted on 15 female and 15 male college students, aged between 18 and 25 years, residing in Lucknow, India. The findings suggest that both male and female participants preferred human-assisted personality reports more than AI-generated reports. To gauge user satisfaction, a 10-item User Satisfaction Scale was constructed. To measure internal consistency, we used the Cronbach's alpha reliability test and estimated weak internal consistency (α = .501). Possible reasons for low reliability could be the inability to account for language preference, interactivity, a small sample size of 30 participants, and heterogeneous items. No significant difference in user satisfaction was found between male and female participants. Subsequent studies should take into account double-blind participation, language consistency, order effect, and homogeneous items for the scale.

Keywords: *AI, personality, Big 5, applied psychology, psychometric assessment*

Artificial Intelligence (hereinafter mentioned as AI) usage and its intervention in different fields are gradually increasing. People are increasingly becoming more self-aware and are understanding technology by trying to learn new and efficient ways of adapting to technological advancements. It has, thus, led to the induction of AI in psychological practice and research.

AI is generally defined as a sub-discipline of computer science that purposefully stimulates programs that simulate human intelligence. Such programs are aimed towards augmenting human intelligence. AI has shown remarkable progress in therapy, connecting human behavior and speech patterns through natural language processing, deep learning networks, and machine learning.

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Recent research studies are pointing towards the need for necessary changes in the procedures and work on the limitations of the methods used by AI. To have a more accessible and better AI intervention in psychological practices, AI needs to learn empathy and user interactivity. Since there are cultural and methodological constraints, AI seems unable to fully substitute for human participation.

Nonetheless, AI has started to contribute to the field of psychology. The WHO released guidelines for the development of safe and ethical AI for health in 2023. "Governing AI for Humanity," a detailed report from the AI Advisory Body, United Nations, was also released in 2024. Several chat bots, mood trackers, predictive analytics applications, and voice analysis features have started to emerge to address common mental health issues like mindfulness, mood regulation, crisis intervention, and self-assessment.

In India, however, people belong to different cultures and ethnicity, and thus, AI usage may vary significantly due to language inconsistency and other factors. For instance, a phenomenon such as "AI authority" is demonstrated, which states that people accept AI decisions, showing full faith and gratitude towards AI even when errors occur (Ghasemaghaei, 2024). This might influence personality assessment preferences in Indians.

Indian society is relatively more collectivist, which emphasizes group harmony and relationships. Whereas, individualistic cultures (in relation to the USA, for example) emphasize more individuality and personal choices (Hofstede, 1980). Cultural differences may consequently lead to differences in personality assessments drawn from AI. AI-powered personality assessments, hence, would require learning cultural differences (for example, semantic equivalence and epistemological differences) and behavioral nuances that may not have been understood well in traditional personality theories.

Paradoxically, AI tools have been presented to have superior perceived empathy compared to human experts in controlled evaluations. Third-party evaluators consistently rate AI-generated responses to be more compassionate, understanding, and validating than responses from crisis intervention specialists and licensed therapists and counselors (Hatch et al., 2025). Licensed mental health clinicians' evaluations have confirmed that AI responses display higher levels of emotional validation and motivational language, though they have also emphasized that perceived empathy differs fundamentally from genuine understanding. Recent evidence has shown that informing participants about AI versus human assessment somehow alters their responses and behavior; they may direct their responses on the basis of perceived assessment purposes and cultural expectations about human versus machine evaluation. The theoretical foundation draws from social intelligence theory (Newell & Shuman, 2024).

Big 5 personality traits depict attitude towards AI, such as higher agreeableness predicting a more positive attitude towards AI tools and conspiracy mentality denoting AI resistance. We can say that personality traits also denote positive or negative attitudes towards AI (Glicksohn & Shemesh, 2025). India's AI healthcare has made several advances in different fields such as telemedicine, automated diagnosis, behavioral assessments, defense, education, and logistics sectors. Moreover, Indian organizations have implemented multilingual AI-generated assessments to accommodate linguistic diversity by integrating natural language processing in order to understand different regional languages and maintain psychometric validity. (MeritTrac Services, 2025, July 28).

The study aims to bridge and integrate the AI capabilities and potential with psychological practices and their methods to help the people worldwide and make mental health services accessible to all. AI has demonstrated a competitive performance with human assessments in empathy and other technical advancements and accurate results; hence, understanding user preferences becomes essential for responsible implementation. The study recognizes both AI's current limitations in understanding human emotions and also considers its potential as a synergistic tool in psychological assessments in order to enable innovative approaches and better implementation of AI in mental health service delivery.

The intersection and integration of AI and psychology has led to the advancement of various opportunities in the field of research and innovation. Traditional methods being followed are well-established methods of evaluating personalities. The purpose of this study is not to disregard the old practices or to replace existing methods, but rather to introduce a new, convenient, and easy method to integrate such practices in the field of psychology. Traditional methods have faced limitations like being time-consuming, subjectivity, personal bias, and scalability. This advancement aims to bring an opportunity for psychologists to make their practices efficient and improve their performance in their careers. With rapid advancement in AI, the tools are now capable of analyzing vast datasets, identifying performance, modifying changes, and assisting patterns and decision-making processes. These capabilities reflect an opportunity to explore new methodologies in psychological assessments.

Our study, which is a quasi-experimental research method, aims to focus on the AI integration in the psychological practices—not to replace humans/existing methods but rather to examine how it can be used as a supportive tool and further increase its utility in the clinical practice. This study specifically considers personality assessment (NEO 5), acknowledging the research gaps, its limitations, ethical considerations, and privacy issues following the APA guidelines.

REVIEW OF LITERATURE

The present study reviewed 20 articles obtained from Google Scholar, Semantic Scholar, and Mendeley that were published during the years 2024 and 2025. These articles were searched using terms like "AI and Psychology," "AI and Personality Assessment," and "AI and Personality Assessment on Indian Population." It highlights their research findings, research gaps, suggestions, and its relevance in our study.

Patil, Shinde, and Nemade (2025) conducted a study that introduced a human-centered framework for building empathetic AI. Their model integrated psychological theory and concepts and used prompt engineering and machine learning to help AI tools to interpret user emotions and provide relevant feedback. The study conducted by Huang and Hadfi (2025) developed multi-observer agents in large language models, which reduced the biases present in self-reported data by enabling several AI "agents" to assess an individual's characteristics collectively. This further helped in enhancing the validity and precision of the personality assessment. Both the studies convey that empathy and collaboration can make AI tools more efficient, effective, and trustworthy. These researchers highlight that empathetic AI should not replace therapists but rather act as an assistant in order to deliver better mental health services.

Kruijssen and Emmons (2025) conducted a study that designed AI agents to display stable, deterministic personalities; their agents used tests such as the Big Five Personality and the Myers-Briggs Type Indicator (MBTI). The study demonstrated that AI agents are able to express consistent traits over time, which further helped in improving user trust and prediction about the future. Additionally, Li, Shi, Yu, and Zheng (2025) conducted a comparative study to evaluate two common personality assessment formats—forced choice and Likert scale. They found out that the forced-choice format led to more accurate and unbiased results since it required AI models to choose between multiple options rather than rating themselves, which further helped in reducing subjective bias and led to an increased trust in AI tools. Piastra and Catellani (2025) evaluated how well GPT-4 estimated human personality traits like openness, extraversion, and neuroticism with high accuracy, although context and emotional tone influenced the results and were considered an important aspect in personality assessment. Considering these studies, we can infer that users are adapting psychometric tools to measure personality traits, consistency, and accuracy. Researchers have used large language models and multimodal data, including language, gestures, facial expressions, and algorithms (search engine optimization), to improve AI-based personality assessment.

However, Islam, Noor, and Abdul Rahman (2025) conducted a systematic mapping study that reviewed different tools for personality and emotion detection. The research findings suggested that although multiple tools exist, they still lack accuracy and data across multiple modalities; hence, developing multi-modal datasets and transparency could significantly enhance the quality of AI models in personality prediction. Moreover, Chishti, Ardekani, and Varastehpour (2024) conducted a study that extended AI personality assessment beyond human users; they used AI models to evaluate the personality of websites by analyzing design features, daily user content, and written content. Researchers demonstrated how AI interprets digital artifacts using psychological concepts.

A study conducted by Rajput, Kharade, Pawar, Wakhare, and Ahir (2025) used multi-modal intelligence to analyze video interviews by using facial, vocal, and textual data to infer personality traits, which helped in the recruitment process during the interview by identifying suitable behavioral patterns. In addition to this, Kovbasiuk et al. (2024) conducted a study on character attributes of early adopters of generative AI technologies. The research findings suggested that people who were less neurotic and more flexible were more likely to try out new AI models, which state that personality affects how people use technology. Kumar, Seewal, Jain and Kaur (2024) developed a framework that made use of AI and personality profiles. Their research findings suggest that patients responded better to treatment plans when personality traits were considered and AI-based therapy recommendations were made. Hence, understanding illness became easier for patients.

A study by Sarsenbay et al. (2025) demonstrated an AI-based job recommendation system to enhance the recruitment process of candidates by matching applicants based on personality traits rather than just skills, which resulted in improved job performance and satisfaction. Moreover, Aslam and Murtaza (2025) conducted a study where they used AI to predict academic performance through student personality traits, identifying students' motivational and emotional needs. Together, these studies show that AI personality assessment has contributed to being effective across professional and educational contexts.

Although AI ethical guidelines are followed, sometimes it might reflect subjective bias and cultural differences among the participants in the study, which may lead to uneven or biased results. To avoid that, and in order to maintain uniformity, a standard and transparent approach must be followed, considering all the ethical and privacy concerns following APA guidelines.

The reviewed studies have shown major progress in the field, but several gaps still persist and require attention. For example, only a few researchers have validated the user satisfaction scale, which compares the human report and the AI report. Also, not many studies have been conducted on the Indian population, covering the individual differences and gender differences that persist and are equivalent factors in the research study, which cannot be missed out. Still, very few studies have been carried out covering the Indian population. In order to detect fairness, studies from different cultures and ethnicity in India need to be explored. Privacy and ethical considerations are also an important aspect that needs to be taken care of at every step in practice and research purposes. Most studies that exist focus on automation rather than cooperation.

Several research studies have taken into account the AI-driven personality reports; still, the factors influencing assessment method preferences are yet to be discovered. Moreover , Indian context, cultural differences, values, hierarchy, and linguistic diversity need more attention and exploration. Future research studies should try focusing on collaborative workflows and integration between AI and human experts to enhance performance and user well-being.
Addressing these gaps will help make AI personality assessment more accurate, ethical, valid, reliable, and beneficial for the people.

METHODOLOGY

In this study, the User Satisfaction Scale (a standardized scale used to measure participants' satisfaction levels on both human-assisted and AI-generated reports) (dependent variable) is operational on the basis of the participants' preference between the human-assisted report (a personality assessment report given to each participant under the supervision of a licensed clinical psychologist) and the AI-generated report (a personality assessment report generated by AI by giving a properly structured prompt that was standard across the research study) (independent variables).

Participants

A quasi-experimental study was conducted on 15 female and 15 male students at Era University, Lucknow. We used convenience sampling, a non-random technique, to select participants who were readily available and willing to take part in the study. The study was carried out in the laboratory at Era University, under the supervision of a clinical psychologist. Consent was taken from the participants, and confidentiality was maintained.

Tools

We have used the following tools:

1. Big Five Personality Assessment Scale (NEO 5)
2. Demographic data of the participants
3. AI tools: ChatGPT and Perplexity
4. A user satisfaction scale to evaluate human reports and AI-generated reports.

To maintain standardized scoring across all participants, we have adhered strictly to the scoring norms of the Big Five Personality Assessment Scale.

Procedure

We asked each participant to complete the Big Five Personality Assessment Scale. After data collection, we performed scoring according to the standard norms of the tool under the supervision of a clinical psychologist. We explained the personality report given by the human to each participant individually in the laboratory setup at Era University. Participants read the report carefully and were then instructed to use the AI tool they were familiar with—either ChatGPT or Perplexity.

They were asked to enter the following prompt as it is: "Generate a concise psychometric report covering Big Five traits with key percentiles and descriptions, motivational drivers, and career fit with strengths, risks, and recommendations. Summarize interpersonal strengths and challenges, predicted psycho-social outcomes, and immediate growth areas like perfectionism, visibility, emotional expression, and focused work. Include a clear developmental road-map to become the best in India, outlining short-, medium-, and long-term goals. Key experts to follow, essential skills and tools to develop." After reading the personality report generated by the AI tool, each participant filled out the user satisfaction scale. To maintain a standard scoring, AI was instructed to follow a set parameter, and more emphasis was given on career, social outcomes, and interpersonal relationships so that it makes sense to the participants. The same was followed in AI delivery as well as the human report. The user satisfaction scale measured satisfaction with both the human-generated and AI-generated reports. Demographic details collected included age, occupation, education, nationality, family income, number of siblings, gender, any diagnosed mental health condition, and marital status. We engineered a prompt for participants to insert and generate in the AI report. We used a standard template for the AI as well as the human report in order to have consistency and a standard scoring. In the template, we used several domains like Motivational Profile, Career Trajectory Fit, Interpersonal and Social Functioning, Psycho-social Outcomes, Immediate Growth Recommendation, and Developmental Road-map Towards Goal. We used these domains since they were a part of personality assessments like MBTI (Myers–Briggs Type Indicator), Holland's RIASEC Model (Career Interest Inventory), StrengthsFinder (CliftonStrengths Assessment), DISC Personality Assessment, the VIA Character Strengths Survey, and 16PF (Sixteen Personality Factor Questionnaire). These renowned tests also explain the domains that we have used in our standard template. Motivational profile that states competence, contribution, recognition, autonomy, and identity of the individual. Career Trajectory Fit that considers Best Fit Roles, Strengths in career, Risks and Recommendations, and Interpersonal and Social Functioning that conveys Strengths and Potential Challenges. Psycho-social outcomes that label positive trajectory, risks, and well-being drivers. Immediate Growth Recommendation that considers Perfectionism Management, Visibility, Emotional Expression, and Focused Signature Work. Developmental Road-map Toward Goal that highlights short-term, medium-term, and long-term goals. These domains were taken since it's important to mention in a Personality Assessment Report. Since the motivational profile considers what naturally excites a person, what they value the most, and what gives them energy and why they behave the way they do, and also these factors affect the way the person behaves in interpersonal relationships and social setups, it also predicts the best-fit career roles depending on their personality traits and their likelihood of performance in those domains later in life by mentioning the developmental road-map towards the goal. It mentions the individual's strengths in their career, their risk factors, and their well-being drivers, which act as a major component in personality. In order to maintain predictable patterns in our reports, we took help of the most vividly used personality tests that exist. Recommendations were given strictly based on the scoring of the Big 5 of each participant under the domains mentioned above; also, no suggestion, diagnosis, or prescription was given to the participants. We followed the ethical standards of the American Psychological Association (APA, 2025) throughout the research process, ensuring voluntary participation and confidentiality among participants.

Statistical Analysis

We have developed the User Satisfaction Scale, and to evaluate the psychometric properties of the User Satisfaction Scale, Cronbach's alpha, which measures internal consistency, was estimated. The Shapiro–Wilk test is used to examine the normality of the data distribution. To analyze gender differences in user satisfaction, appropriate tests will be applied based on data normality: an independent samples t-test and the Wilcoxon rank-sum test were measured.

Ethical Considerations

The study was conducted following all the ethical guidelines and norms given by the APA. It was conducted under the supervision of a clinical psychologist, ensuring transparency and informed consent. Also, no diagnosis, prescription, or suggestion was given to the participant. It was made sure that the researcher asked no personal questions and no counter-questioning or follow-up questions were made from either side. Emphasis was made on career guidance, goals, and interpersonal relationships. Consent was taken from the participants at first to ensure ethical guidelines. A set parameter was followed to ensure consistency and standard scoring to allow sense-making for the participants.

RESULTS

For the overall result, considering the total score of the user satisfaction scale, we have used Cronbach's alpha test to administer internal consistency in order to measure the reliability of the scale.

Table 1: Showing Cronbach's alpha reliability score based on the overall (10 items) scores of the user satisfaction scale.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of Items
.501	.490	10

In overall scoring, Cronbach's Alpha score is .501. This score represents poor internal consistency.

Table 2: Showing Cronbach's alpha mean score item-wise and their correlation.

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
S1	31.80	14.924	.156	.275	.489
S2	30.83	13.799	.327	.287	.442
S3	31.60	14.248	.153	.383	.494
S4	30.97	16.516	.110	.528	.563
S5	32.23	14.047	.257	.340	.460
S6	32.13	16.189	.066	.423	.551

S7	**31.13**	**14.257**	**.162**	**.496**	**.490**
S8	**31.27**	**11.995**	**.479**	**.529**	**.375**
S9	**32.03**	**12.585**	**.355**	**.577**	**.420**
S10	**32.2**	**12.786**	**.423**	**.616**	**.405**

Both the tables above show the overall score of the user satisfaction scale, covering the total scores of all 10 items.

Subscale Cronbach Alpha Reliability Score

We have measured the reliability of the sub- scales (human-preferred scores and AI-preferred scores) separately using the Cronbach's Alpha Test to find out the internal consistency.

Table 3: Showing Cronbach's alpha reliability score on 4 items (Human Assisted Report).

Cronbach's Alpha	Number of Items
.636	**4**

Table 3 measures the responses given by the participants in items 2nd, 4th, 7th, and 8th of the User Satisfaction Scale that recorded the human-preferred report of the Personality Assessment. A total of 4 items were used in the user satisfaction scale for the human report.

Table 4: Showing the Cronbach's alpha reliability score on 6 items (AI-generated report).

Cronbach's Alpha	Number of Items
.568	**6**

Table 4 measures the responses given by the participant in items 1st, 3rd, 5th, 6th, 9th, and 10th of the User Satisfaction Scale that recorded the AI-preferred reports of the Personality Assessment. A total of 6 items were used in the user satisfaction scale for the AI report.

While considering the sub-scales of the User Satisfaction Scale, the Cronbach's alpha score is .568 for the AI-generated report and .636 for the human report, which denotes a slightly better reliability of the human report scale (Table 3) than the AI report scale (Table 4) and the overall scale (Table 1).

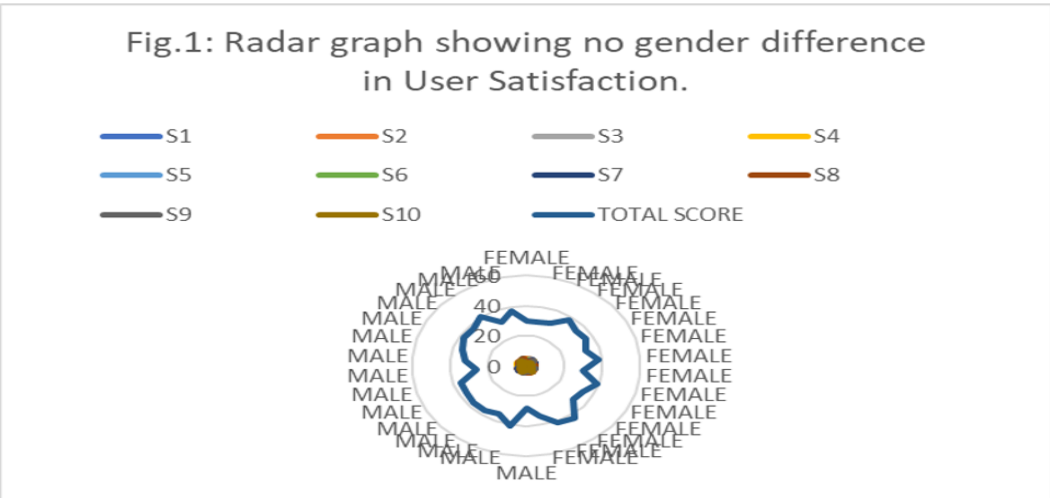

Fig. 1: Radar graph showing no gender difference in user satisfaction.

Table 5: Showing gender differences in user satisfaction (T-test).

	Responses given by females	Responses given by males
MEAN	35	35.133
VARIANCE	16.857	16.838
OBSERVATIONS	15	15
Df	28	
T Stat	-0.088	
P two-tail	0.929	
T Critical two-tail	2.048	

An independent sample t-test revealed no significant difference in User Satisfaction scores between female (M=3.00, SD=4.10) and male participants (M=35.13, SD=4.10).

t (28) = -0.09, p = .93, which is greater than the alpha level of 0.05; hence, user satisfaction levels of males and females are statistically similar, and any small difference in their scores is likely due to random sampling variation rather than a real gender effect.

DISCUSSION

The purpose of the study was to evaluate the user satisfaction and preference of the participants between a human report and an AI-generated report on the Big 5 Personality Assessment. The experiment was a preliminary exploratory lab study that had no correlation among the variables.

The findings show that females preferred the human report over the AI-generated report (t-Stat=-0.08<t-Crit=±2.05), and males also preferred the human report over the AI-generated report. Overall, both genders were more inclined towards human reports for their personality assessment.

The possible reasons for choosing the human report over the AI report could be (α = .636) that the participants were not active AI users who interacted and shared their personal information with AI tools; hence, they did not find the AI report more engaging and friendly than the human-assisted report. The time exposures of the human-assisted assessment report and AI-generated report were not the same. Instead, the human report felt more interactive and was perceived as more of a guidance and counseling resource. Participants felt more emotionally connected with the human report than the AI-generated report.

However, the study could not take into account the order effect—presenting the human report and then the AI-generated report. At first, the human report was explained to the participant, and then the AI process was introduced. Further, the local participants were not native English speakers, and the language of the report was in English, which could have created a language barrier in understanding the report better. Since the medium of the human report was a verbal explanation followed by the physical copy of the report and the medium of the AI report was a written report on their devices, the participants might have understood the human report better due to human interaction. The participants were all the students of Era University, Lucknow, from different departments who were willing to be a part of the study. Such results might have been due to a small sample size. Also, for generating AI reports, participants used their personal devices (ChatGPT), which could have led to different report generation ranging from person to person depending on their AI usage. User history and usage behavior may not be the same across participants.

Further research studies, supported by Patil, Shinde, and Nemade (2025) and Huang and Hadfi (2025), show that empathy and collaboration can make AI systems more human-like and trustworthy. If AI is integrated into counseling and clinical practice, it has to be more interactive; two-way communication is required between AI and the user.

Since India has a great population and diverse ethnicity, any AI model that will be used for mental health services would require learning all different languages; hence, AI needs to be trained to be culturally sensitive. Not much research has been done on the Indian population and, more precisely, on the user satisfaction scale. AI has the potential to be trained and cater to the mental health services in India by enhancing its interactive features.

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Conflict of Interest

The author(s) declared no conflict of interest.

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