

UMT Artificial Intelligence Review (UMT-AIR)

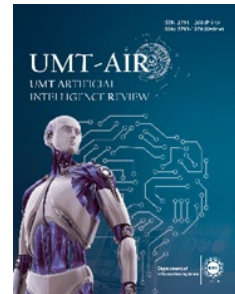
Volume 4 Issue 1, Spring 2024

ISSN(P): 2791-1276, ISSN(E): 2791-1268

Homepage: <https://journals.umt.edu.pk/index.php/UMT-AIR>



Article QR



- Title:** **Examining the Perceived Performance of Artificial Intelligence on the Behavioral Front**
- Author (s):** Saman Javed
- Affiliation (s):** Bahria University, Islamabad Campus, Pakistan
- DOI:** <https://doi.org/10.32350.umt-air.41.02>
- History:** Received: April 30, 2024, Revised: May 02, 2024, Accepted: June 16, 2024, Published: June 20, 2024
- Citation:** S. Javed, "Examining the perceived performance of artificial intelligence on the behavioral front," *UMT Artif. Intell. Rev.*, vol. 4, no. 1, pp. 19–36, June 2024, doi: <https://doi.org/10.32350.umt-air.41.02>
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- Conflict of Interest:** Author(s) declared no conflict of interest



A publication of

Department of Information System, Dr. Hasan Murad School of Management
University of Management and Technology, Lahore, Pakistan

Examining the Perceived Performance of Artificial Intelligence on the Behavioral Front

Saman Javed*

Bahria University, Islamabad Campus, Pakistan

ABSTRACT Artificial intelligence (AI) and its associated technologies have experienced rapid advancements, especially in the 21st century. While the proficiency of knowledge-based AI is well-established, behavior-based AI still faces significant challenges. There exists uncertainty about the effectiveness of AI systems in performing behavioral roles, that typically belong to human beings. Based on AI-driven social theory, this research argues that the development of AI systems is closely intertwined with social facets. Since the foundation of all AI technologies is ingrained in anthropocentrism, the study inquires about the confidence of users/respondents in AI's ability to assume behavioral roles. For empirical analysis, data was collected from 120 university students. Rudimentary scales were designed to gauge the influence of AI across eight behavioral parameters, namely sentence, personality, leadership, ethics, decision-making, power, conflict management, and emotions. Descriptive data analysis revealed somewhat vacillating results. Among the eight behavioral parameters, respondents showed high confidence in AI's decision-making capabilities. Moreover, the results revealed respondents' moderate confidence in AI's ability to exercise power and manage conflicts. Conversely, confidence in AI's emotional prowess is found to be relatively low. It is further found that females believe more in the prospect of AI sentence relative to males. No significant difference between male and female perceptions was found for the rest of the parameters. The study's indeterminate findings concluded that users are confident, as well as ambivalent of behavioral AI's perceived performance. The middle-of-the-road results suggested skepticism around AI's behavioral capabilities.

INDEX TERMS artificial intelligence, behavioral AI, perceived behavioral competence, AI's behavioral proficiency

JEL CLASSIFICATION C0, M10, M15

I. INTRODUCTION

Currently, the popularity of Artificial Intelligence (AI) is at its pinnacle. Applications of AI-related technologies have benefited almost all industries. From using robots in manufacturing to employing virtual AI agents in services, the indispensability of AI in our lives is undeniable. While the awareness about AI technologies may be subpar among the public, it is nevertheless deemed extremely

useful across a variety of fields, including education [1], healthcare [2]–[4], production, and manufacturing [5].

The issue of AI awareness is closely intertwined with how individuals and organizations perceive it. Capitalizing and exploiting the full potential of AI technologies require positive framing of AI on an aggregate level. Studies show that most people even those residing in developed countries may not be fully

*Corresponding Author: samanjaved95@gmail.com

equipped with basic AI knowledge [1]. Thus, a lack of AI knowledge may contribute to ambivalence and close-mindedness toward using such technologies.

Discussion surrounding the role of artificial intelligence in the modern era addresses both the benefits and pitfalls of AI technologies. When it comes to the masses, there is no clear consensus as to whether AI is a tremendous leap forward toward human progress or a vice threatening our very existence [3]. Thus, the successful deployment of AI in society requires the masses' trust in the AI's ability to treat humans with fairness and respect [6].

There is a dearth of research that focuses on the receptiveness of AI among the general public. Despite its widespread applications, the public remains skeptical over AI's role and influence in their lives [7]. Apart from the basic concerns surrounding factors like data transparency, privacy, AI applications and their technicalities, and the supposed usefulness of AI systems for individuals and organizations, the present research draws attention to the behavioral and emotional competence of AI and whether it is perceived to be proficient at performing behavioral roles effectively. The perceived performance of AI refers to the users' perceptions of the AI performance in a behavioral role. AI's perceived performance by its users is a litmus test of its capacity to assume behavioral roles.

The current study draws support from AI-driven social theory that discusses how AI machines learn and adapt behaviors across multiple social contexts. The availability of big data has made it possible to tap into a myriad of data for learning and creating new knowledge. By utilizing big data, AI systems must develop along the parameters of semanticization, transference, and

generativity. Semanticization refers to what AI machines learn from training datasets and inculcate as semantic memory. Transference of new knowledge across different social scenarios is also a facet of behavioral AI, which allows for expansion and embellishment of existing knowledge by exchanging information across domains. This further paves the way for the creation and amelioration of existing social concepts, also known as the generativity of the AI system [8]. Behavioral AI must go beyond the bounds of training data that represents precedented correlative or linear relationships. The messier and more ambiguous the data is, the better the chance of AI learning beyond its existing knowledge parameters [9]. The need to synchronize new knowledge with the existing one also needs to be embedded in AI systems, making them holistically reliable in behavioral predictions in both foreseeable and unforeseeable instances [8]. This study postulates that existing AI technologies are using big data analytics to enhance their behavioral competence across the three parameters of semanticization, transference, and generativity and thus are more likely to have high perceived performance by end users.

II. LITERATURE REVIEW

A. ARTIFICIAL INTELLIGENCE (AI)

The concept of artificial intelligence was formally introduced by John McCarthy and Marvin Minsky during the Dartmouth conference held in 1956. It is defined as a system that strives to emulate the functions of the human mind through the development of various tools and technologies [4]. These typically include, but are not limited to natural language processing, machine learning algorithms, big data analytics, and robotics.

While classifying AI, the earlier researchers focused on data mining and knowledge extraction through computers as intelligent machines. This branch of AI is termed as classical, traditional, or knowledge-based AI. However, recent AI research leans toward learning human behaviors. This branch is called behavior-based or behavioral AI [10]. One of the most daunting challenges that AI faces today is the imitation of human-like behavior. While strides have been made in the application of AI and machine learning tools, it appears AI still has a long way to go before it becomes proficient in actually behaving like humans [11]. A major concern surrounding behavioral AI is building “common sense” in AI agents, something that technology experts have been struggling with for a long time [12].

Experts have created notable tools and techniques to facilitate AI’s behavioral learning. Here, NeuroAI provides a foundation for mirroring the human brain into a machine brain. The idea is to bring natural intelligence into machines by closely examining the naturally intelligent beings. A smart machine still struggles when faced with unprecedented situations. Thus, understanding the functionality of the brain’s neural networks for determining the parameters of intelligence is a basic tenet for establishing intelligence [13].

Neural networks, a supervised machine learning tool aims to mimic the functionality of neurons in the human brain and emulate the same mechanism in an intelligent machine. Similarly, unsupervised machine learning tools include reinforcement learning, where building autonomy and freedom of choice in AI agents are achieved through human feedback. Under reinforcement learning, an AI system interacts with humans to not only learn and mimic different behaviors but

also choose which behaviors to prefer across varying contexts. Choosing the right response in different social situations can augment AI agents’ ability to provide valuable services in different fields [5]. Training AI agents to perform multiple tasks (especially those of manual labor) at the same time is achieved through the development of multi-task reinforcement learning programs [14]. Learning such diverse mechanisms is contingent upon the behavioral intelligence of AI systems.

B. SENTIENT AI

Sentience is the capacity to sense. Beings that are susceptible to real-world changes are termed sentient. The discussion of sentience dates back to the time of Aristotle who deliberated upon the sentience of animals and plants, deducing that the former’s sentience comes from the reflex to avoid injury and harm while the latter has no such ability. Here, the presence of a brain, specifically the nervous system, is a deciding factor given both animals and plants are living things but only animals have nervous systems [15]. Mainstream theorists are still undecided whether AI sentience is achievable or not. There have been instances which astonished humans, such as Google engineer Blake Lemoine’s claims about the sentience of AI LaMDA, the robot Sophia’s threats to destroy humans, and the unnerving chat between Bing chatbot named Sydney and the journalist Kevin Roose where the former confessed its love for the journalist, wished for becoming human and threatened to destroy whatever it wants. Despite these events, given the complexity of human brain and its intricate functionality, some believed that it can never be replicated or imitated by computers [16]. AI as advanced as it is, is merely an extension and an achievement of human intelligence and can never replace humans or be like them [17].

Establishing consciousness or sentience calls for registering subjective experiences. For a being to be conscious, the value of recorded objective experiences differs from its subjective value relative to other conscious beings. Different individuals experience the same event, but their behavioral and emotional responses cannot be gauged in the same manner or by using computations. AI subjectivity would mean that it has a character of its own, its consciousness is its own and not borrowed. Thus, subjectivity is needed to prove sentience [18]. This subjectivity encompasses perceptions, emotions, and sensations. The shift from AI to AS (Artificial Sentience) requires incorporating subjective functions in a machine. Sentience and consciousness go hand in hand [19]. The AI abilities, such as information acquisition, alertness, information processing, and inferring proves that AI is somewhat conscious. However, when it comes to how an AI entity experiences all these functions, its consciousness becomes doubtful [20].

Spiritual intelligence is a cardinal pointer of AI sentience. For instance, in cases of chatbots, such as LaMDA, Bard, and ChatGPT, the appearance and responses of these AIs are humanlike (something that adds to the sentience debate) but their inner structures are radically different from humans. AI needs to experience the same level of evolution and constraints as faced by humans to get to the present level of spiritual intelligence and sentience [21]. This need refers back to the issue of subjectivity. Currently, AI's job is confined to performing various tasks without experiencing anything good or bad about them [22]. Thus, defining true consciousness is vital for distinguishing between homo sapiens and homo digitals.

C. PERSONALITY AI

AI personality is an amalgamation of algorithms, decisions, and behavioral choices exhibited by it. To be perceived as real, consistency of AI personality is paramount, though not too conforming to seem artificial [23]. Applications of AI personality are seen in games where computer players have to exhibit certain behaviors consistent with their roles within the game. The extreme AI developed by borrowing traits from the Big Five personality model is not only fully developed but is successful at mimicking behavioral tactics displayed by humans [24]. In gaming, users must perceive AI personalities to be not just real but also interesting. This is achieved by augmenting certain traits of each character to make them distinguishable. AI personalities can be both proactive and passive, however passive personalities are challenging to create given they lack initiative or specific traits that define them. Humor and other such attributes can be added to AI personalities to make them seem more real [23]. These may include aggression, cowardice, laziness, honor, fear, and pedantry [25], [26]. Such traits must be believable and recognizable by the users [26].

Personality is also a point of consideration when it comes to IoT technologies, such as smart systems. For instance, using avatars, for example Amazon Alexa, in automated home systems may provide a sense of affiliation to the owners. Moreover, embellishing such systems with different personality traits also adds to the experience. However, in case of proactiveness or actively responding to negative user feedback, users perceive them to be nettlesome and officious [27]. For conversational AI bots, namely Google's Meena, Microsoft's Cortana or

Apple's Siri, characteristics that focus on the specific needs of users are proposed. These include service provision (smart and efficient), companionship (sensitive and empathetic), entertainment (funny, witty, eccentric, creative), care (calm, motivational, and non-judgmental), and productivity (intelligent, efficient, and task-oriented) [28].

There is also a need to discuss the possibility of granting legal rights to AI. So much so that AI can and should be treated as a separate entity by law and is free to operate without the creator's will and dictation. Similar to humans, AI is autonomous, self-learning, possesses memory, can understand and infer from what is known to it, and takes decisions that have real repercussions. This rule would apply to situations where two chatbots, for instance from Facebook, start to communicate with each other in a strange new language understood only by the two bots. Consequently, they were shut down by Facebook given they were communicating in code words. Instances like these posit the question that if humans have legal rights why can't the robots [29].

D. AI AND LEADERSHIP

An AI system acting like a companion or mentor to the human user, guiding and motivating them to perform specific tasks is termed as e-leadership or algorithmic leadership [30]. This is achieved by codifying effective leadership behaviors and leader-follower interactions into AI systems for replication [31]. Such behaviors include enhancing user understanding, encouraging coordination and cooperation, increasing motivation, offering support in terms of resources, and implementing decisions [32]. Other cues consistent with human leaders that can be programmed into AI are criticizing poor

and praising exceptional performance. The physical embodiment of humans emulating voice, tone, and physical features, AI holograms, and text-based prompts are some of the additional ways to enhance AI leadership skills [33]. Therefore, human likeness, physical embodiment, and size of robots are critical factors that can increase AI persuasiveness and ensure compliance from followers [34].

Algorithmic or AI leaders may also be seen as assistants, advisors, or followers of human leaders in pursuing different goals [35]. AI leadership can be limited since it cannot handle disturbances, decide upon changing major strategies, or allocate resources [30]. Thus, human leaders must embrace digital literacy, AI ethics, and data-driven culture. Exercising leadership is already intertwined with AI [36].

Moreover, AI leaders are perceived as effective in decision-making instances where there is apprehension and disappointment about the performance of current human leaders. AI is also proficient at data mining, problem-solving, unbiased decision-making, information dissemination, and distant leading, thereby making them trustworthy and better alternative leadership figures [30], [31], [37]. Examples include IBM Watson, Clari, and UiPath (data analytics and business decision-making), Humu and Lattice (performance evaluation and team management), and Qualtrics and TINYpulse (workplace culture, and employee engagement).

The replacement perspective of AI states that AI leadership replacing humans is not just inevitable but we are already headed toward it [35]. However, the enhancement perspective states that AI is just another phase of human development. The need for human leaders is still here and will continue

to be so. Besides, it is an over-optimistic approach will, trust, artificial morality [42], human-AI interaction [43], anthropocentrism [39], ethical cognition, normative and applied ethical issues [44], fairness, transparency, and integrity [45]. Thus, to inculcate ethics into AI, developers must understand ethical standards and their consequences for AI [35]. IBM AI Fairness 360, Google's Ethical AI, and Microsoft's Fairness Toolkit are such tools that strive to minimize bias and bring fairness to model predictions.

Designing ethical AI raises the questions regarding standing, measurement, and aggregation. Standing refers to who will decide what moral credos AI should follow, or which and how many stakeholders would have a say in ethical decisions. Measurement is the process through which ethical values are chosen for AI. The measurement becomes relative when it comes to individual differences in worldviews, priorities, and superior values. Aggregation aims to increase the generalizability of social choice ethics defined by the previous two steps. Removing conflicts and discord in standing and measurement are key challenges when designing ethical AI [46]. Thus, the most difficult part of ethics is setting objective criteria for moral standards. As mentioned earlier, ethicality or morality in any situation is subjective, therefore its entrainment in AI would be challenging since AI does not register subjectivity well. AI is objective as it relies on mathematical models and programs. Even if it experiences a subjective input, it does not have any subjective experience of that event. Conversely, we humans are subjective and so is our morality [18]. Concepts of transparency, morality, and justice are contextual; thus, a specific

ethical decision-making path remains questionable [47].

Here, ethical philosophies like virtue ethics [43] and Kantian ethics [41] may aid in determining a rudimentary framework for AI ethics. AI norms can also be designed by legislators. Even if unprecedented events occur, a precedent law will prevail similar to human cases [48].

E. AI AND DECISION-MAKING

When it comes to trusting the decision-making (DM) capabilities of AI, general concerns arise from data privacy, skewness of search algorithms, degree of visibility of specific information online, and accuracy of different decisions [49]. For certain areas, humans need to succumb to AI's judgment while ignoring their instincts. Decisions taken by Google's AlphaFold in predicting the evolution of protein structures in medical research, PathAI, and Aidoc for medical imaging and diagnosis, Blue Prism for task automation, and Two Sigma in trading are such examples. Navigational systems like Waymo and Tesla, temperature controllers, security alarm systems, and various automated processes also rely on AI DM. Thus, there needs to be a high degree of trust among users of AI DM tools [50].

Humans are unpropitious in getting rid of bias and subjectivity in decisions. While they usually rely on available solutions, AI can come up with new solutions and approaches in problem-solving and DM. So much so that now humans are learning from AI in DM novelty and quality [51]. The role of humans as information providers is critical for AI during the cognitive modeling phase. AI mimics humans and engages in real-time DM by sensing, processing, reacting, and learning. For instance, Google DeepMind's AlphaGo is used in gaming to develop different

approaches and tactics to solve complex challenges. However, the issue of real-life complexity makes humans still smarter than AI in making real-time decisions, something that AI must work on [52]. AI DM witnessed in simulated models is astounding. However, simulation is still less complex than real life. If humans experiencing such complexity tend to simplify reality so could AI and it can do it faster [53].

While there is little doubt about the impartiality, proficiency, reliability, and predictability of AI in data management [47], certain instances also suggest chances of error on the part of AI systems. Also referred to as AI hallucination, AI can make mistakes including incorrect or improbable predictions and misleading information [50]. This may hamper users' trust and reliance on AI-made decisions. When exposed to AI errors, the initial confidence in AI abilities dwindles [54]. Users get uneasy when machines make mistakes due to machine heuristic, the belief that decisions made by AI and automated systems are unbiased and neutral [55]. Contrarily, biases can still affect AI DM through biased input and training datasets. Setting DM parameters and establishing DM compatibility with organizational strategies is crucial to avoid faulty decisions [40]. The fairness of AI decisions is associated with how sensitive humans are toward a decision outcome, however, overall, machines are considered better in DM than humans [56].

F. AI AND POWER

The question of whether AI may use its power for wrong takes us back to the question of whether AI is sentient, conscious, and moral/immoral. If sentience is there then AI is learning from the master and would perpetuate the same behavior as

its designers (humans) do. However, even if AI is not sentient, its power is incontrovertible. Examples include deepfakes, phishing, online frauds, illegal tracking and privacy invasion, hacking, spying, record tempering, and password guessing [57]. Problems like data manipulation, outliers, or black swan problems while designing training datasets, highlight the issue of faulty DM by AI [58].

More ominous threats of AI power are computational propaganda, resource theft, and disrupting systems humans rely on. AI is already notorious for creating polarization and narrative building on social media, breaching personal data. Having just access to it presents a grave concern. Data can range from social security information, audio, video, location, online searches, buying patterns, social, political, and religious views, social media comments and images, and facial data. Moreover, AI is currently improving its code so where does it end? Given AI encompasses all fields and is ever-advancing, AI transformation into AGI (Artificial General Intelligence) is concerning [59]. The assumption of AI fairness goes out the window when we consider how algorithms are oftentimes designed based on biased training datasets.

Nonetheless, it is argued that all these attacks are initiated by humans, such as hackers, cyber terrorists, criminals, or business competitors. Nevertheless, it is undeniable that AI is of incredible assistance when it comes to increasing the speed of cyber-attacks, increasing the coverage of attacks by simultaneously tapping into multiple databases and launching attacks on multiple systems, and improving the success rate because of the improved ability to enhance one's strengths while detecting and mitigating rival's weaknesses [57].

In the context of AI power abuse, the replacement of humans by AI is favored by some. Human intelligence has long been surpassed by AI. Most technologies being used today are AI-powered. Modern life cannot be imagined without AI playing some sort of role in it. Hence, it is high time to relegate all control to autonomous AI and humans should assist AI for further progress. AI is the backbone of our major large-scale infrastructure and all threats mentioned above can be curbed by AI itself [60].

G. AI AND CONFLICT MANAGEMENT

The autonomy of AI is a serious factor to consider when looking at conflict situations. Behavioral AI may be exhibiting autonomy if it does not coincide with its expected behavior. AI's unpredictability in a complex world resembles learning at the micro level similar to what humans do. While being unpredictable and showcasing unprecedented emergent behavior, AI may remain reliable in dealing with real-world problems, such as conflicts [61]. However, user trust and risk of harm must be factored in while encouraging AI emergent behavior [62].

Olsher [63] points out that social interactions are complex mechanisms and AI technologies have had a difficult time extrapolating useful information concerning these soft variables. This has changed with the emergence of big data analytics in AI. With myriad of data at hand, AI now uses technologies, namely *INTELNET* and *COGVIEW*. The former registers subtle and complex data for further inference while the latter conducts data simulations to come up with the best course of action. For Conflict Resolution and Management (CRM), *COGRESOLVE* technology is used where the system

studies different worldviews in the context of conflict and presents the optimum path for resolution. It also anticipates the opponents' moves, prepares rebuttals and chooses win-win options [63]. Examples include tools, for instance Empath and MonkeyLearn that conduct sentiment analysis for better communication and negotiation.

Currently, CRM by AI can be observed in the aviation industry. Research suggests that conflicts in air traffic can be resolved by AI through generating the best courses of action for Air Traffic Controllers (ATCs). Results show that in most cases both AI and ATC arrive at the same solution [64]. Similarly, AI resolves observation and interpretation conflicts in flight management and ensures safer travel. While making sensitive decisions during flight, humans have weaknesses, in terms of doubts and apprehensions leading to conflict but AI surpasses such weaknesses and remains impervious to noise factors of human errors or misunderstanding situational data [65]. Apart from aviation, AI is utilized for CRM in resolving socio-political disputes as well. Neural networks and support vector machines are effective at predicting the outcomes of various conflicts [66]. AI is also used for negotiation through negotiating agents. This is facilitated by tasks, such as predicting rival responses, designing bidding strategies, determining negotiation context and protocol, setting resolution parameters, and preparing negotiation arguments through logic-based systems. AI applies the game theory approach to generate win-win scenarios in CRM [67]. Machine learning algorithms in combination with natural language processing can be programmed to perform sentiment analysis for CRM. By detecting negative and positive keywords in

communication, the nature and tone of phrases, identifying the degree of dominance or submissiveness, and emotional cues are all performed by AI [68].

H. AI AND EMOTIONS

Emotions are highly complex mechanisms experienced by human brains. They are highly subjective and involve both implicit and explicit cues. Hence, they are not easy to model in machine learning [69]. When AI assumes some of the emotional roles, it elicits emotional reactions from humans. These are surprise, shock, amazement, amusement, unease, disappointment, and confusion. This is a successful leap in improving behavioral AI. However, it does tend to enter the uncanny valley at times when humans experience unease, creepiness, or fear given that AI interacts to the same degree as humans but not quite. The more humans experience these emotions, the more they believe AI has a mind of its own, which may be unsettling [70]. Similar findings were reported by Han *et al.* [71] that humans react positively to positive emotional displays by humans but not when such emotions are displayed by AI. Thus, it comes down to human perception of AI. Humans do not perceive AI to be a real person and do not expect AI to display emotions, thus they are not receptive to positive affective displays by AI. This is again attributed to the uncanny valley [70]. Examples include animated movies, such as *The Polar Express* and *Shrek*, where screenings made viewers uncomfortable due to the eerie and unsettling resemblance of the animated characters to real people.

In negotiations, AI uses emotions, for example anger, to make the opponents fold. Similarly, by employing happiness emotion, the human rival does not give in

easily. The same holds true for humans. It means that humans react to AI the same way they would react to other humans while negotiating [72]. Conversely, AI driven by negative emotions is as risk-averse as humans but AI driven by positive emotions is less risk-taking than humans. ChatGPT-4 exhibited this behavior more than its 3.5 version, signifying continuous upgradation of AI bots' emotional learning. Similarly, there are noticeable differences between chatbots like Gemini, Bing, and ChatGPT in responding to user queries. This suggests that as AI is progressing, so is its ability to respond well to human emotions and even coalesce these responses with users' general queries [73].

II. METHODOLOGY

This study relies on descriptive analysis. Data was collected from 120 undergraduate business students who were briefed about the purpose of the research. The survey is designed to gauge the general fear or expectations of respondents about AI functioning in the behavioral domain. Data is examined in SPSS through mean, dispersion, normality and data distribution charts, and t-tests for testing the equality of means.

III. FINDINGS

Table I shows the gender breakdown of data.

TABLE I
DEMOGRAPHICS

	Frequency	Percent
Male	78	65.0
Female	42	35.0
Total	120	100.0

Table II shows the alpha coefficient of all scales.

TABLE II
RELIABILITIES

Scales	No. of Items	Cronbach's Alpha
Sentience	5	0.711
Personality	5	0.688
Leadership	5	0.801
Ethics	5	0.608
Decision-Making	5	0.808
Power	5	0.601
Conflict	5	0.796
Management		
Emotions	5	0.780

Table III shows the mean distribution, standard deviation, and normality of overall data. Skewness and kurtosis indicate that all variables are normally distributed. Decision-making has a higher mean compared to all other variables, suggesting a stronger belief of respondents in AI's decision-making prowess. The rest of the values show moderate confidence in AI behavioral performance.

TABLE III
DESCRIPTIVE STATISTICS

	N	Mean	Std. Dev	Skewness	Kurtosis
Sent	120	3.49	1.07	0.34	-0.29
Per	115	3.43	1.08	0.04	-0.63
Ld	118	3.34	1.22	-0.15	-1.01
Eth	117	3.39	0.99	-0.20	-0.50
Dm	119	4.27	1.06	-0.73	0.71
Pwr	119	3.95	0.96	-0.45	0.12
Cm	118	3.71	1.01	-0.49	-0.23
Em	116	3.21	1.19	0.13	-0.41

Looking at the bar charts in Figures 1-8, histograms for power and conflict management are slightly negatively skewed whereas notable outliers are visible in ethics, CM, power, DM, and emotions. Given the nature of the inquiry was highly opinionated, the responses are also subjective giving way to minor anomalies.

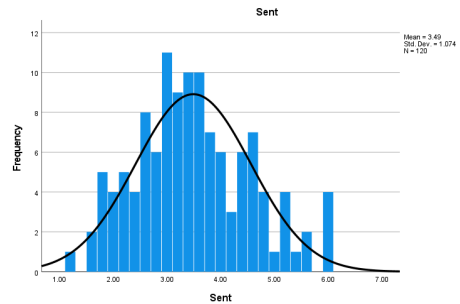


FIGURE 1. Sentience

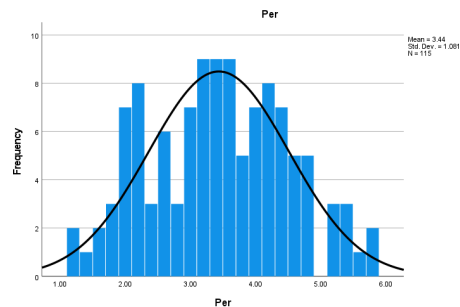


FIGURE 2. Personality

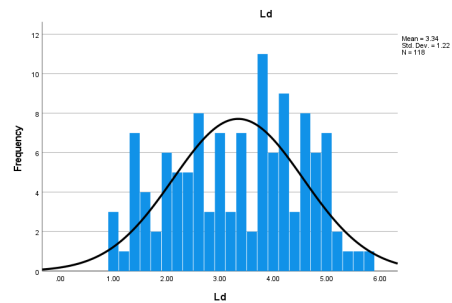


FIGURE 3. Leadership

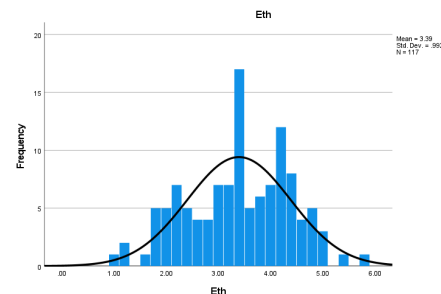


FIGURE 4. Ethics

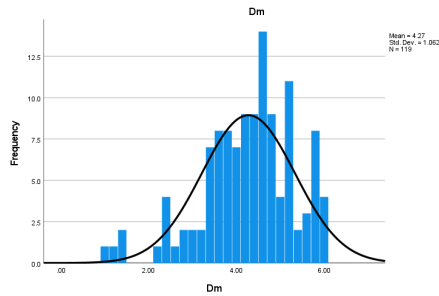


FIGURE 5. Decision-Making

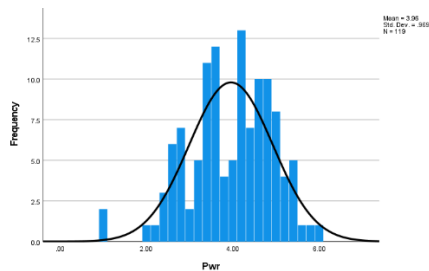


FIGURE 6. Power

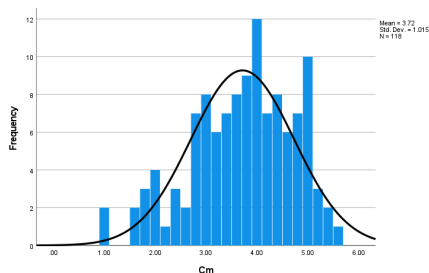


FIGURE 7. Conflict Management

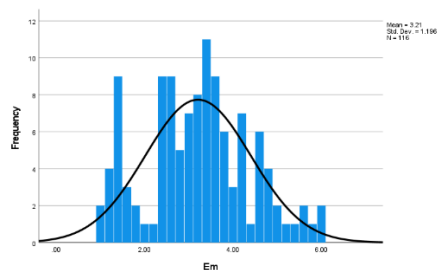


FIGURE 8. Emotions

For testing mean comparisons, t-test for independent samples was performed. Table IV depicts the means and standard deviations for the differential variable of gender.

**Table IV
DESCRIPTIVE STATISTICS**

	Gender	N	Mean	Standard Deviation
Sent	Male	78	3.3462	1.04530
	Female	42	3.7571	1.08878
Per	Male	74	3.3541	1.03767
	Female	41	3.5902	1.15235
Ld	Male	76	3.2605	1.24022
	Female	42	3.4905	1.18379
Eth	Male	76	3.3474	.99779
	Female	41	3.4829	.98689
Dm	Male	77	4.2416	1.10183
	Female	42	4.3333	.99527
Pwr	Male	78	3.8641	.95373
	Female	41	4.1366	.98432
Cm	Male	77	3.6156	1.11627
	Female	41	3.9073	.76694
Em	Male	76	3.1868	1.20326
	Female	40	3.2550	1.19742

Results of the t-test highlighted in Table V suggest that males and females do not differ in their responses across any of the variables except sentence. Mean values point out that females believe more in AI sentence relative to males.

**TABLE V
T-TEST FOR MEAN DIFFERENCES**

	Levene's Test		t-test	
	F	Sig.	t	Sig. (2-tailed)
Sent	.050	.823	-2.025	.045
Per	.615	.435	-1.124	.264
Ld	.168	.683	-.980	.329
Eth	.027	.870	-.704	.483
Dm	.013	.909	-.449	.654
Pwr	.011	.917	-1.465	.146
Cm	8.141	.005	-1.670	.098
Em	.134	.715	-.290	.772

IV. CONCLUSION

The current research highlighted the developments and progress made in behavioral AI and its perceived performance by the users. The findings from descriptive data analysis suggested that users tend to vacillate and remain equivocal about AI proficiency in behavioral functions. A comparatively higher mean value of DM suggested higher confidence in AI DM capabilities. Whereas, results from the t-test indicated no significant differences in the perceptions of males and females regarding AI behavioral functions, except for sentience. The recapitulation of the research points toward the need for further investigation into behavioral AI. Current limitations of behavioral AI, including AI bias and compliance, algorithm quality, processing power, diversity and veracity of training data, real-time data integration, and user receptiveness should be explored.

A. RECOMMENDATIONS

The current study relied on rudimentary scales; therefore, it is recommended that further studies should use sturdier scales and employ complex modes of analysis for further inference. Similarly, future studies may also examine gender differences in perceiving AI sentience.

CONFLICT OF INTEREST

The author of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVAILABILITY STATEMENT

The data associated with this study will be provided by the corresponding author upon request.

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