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Brains, Bond, and Belief: What Sustains Gen Z's Use of AI Assistants

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Abstract: ***With increasing use of personal AI assistants in everyday life, an understanding of the psychological factors that drive their sustained use, especially among the most tech-savvy Generation Z, is necessary. The present research investigates the functions of perceived AI intelligence, anthropomorphism, and trust in AI in shaping the sustained adoption of personal AI assistants by Gen Z users. On the basis of data obtained through surveys from 170 Indian Gen Z, 131 usable responses were retained for the analysis. The research is grounded in the Stimulus Organism Response (SOR) model. Partial least squares structural equation modeling was used to test the proposed relationships. The findings indicate that anthropomorphism and perceived intelligence significantly enhance trust in AI, which in turn significantly predicts the intention to keep using it. While perceived intelligence has direct and indirect effects on usage, trust fully mediates the effect of anthropomorphism. This work adds to the AI adoption body of knowledge by highlighting trust as an important psychological process linking user perceptions to long-term behavior. It also provides developers with helpful guidance on designing AI systems that are emotionally and cognitively engaging, particularly in quickly growing digital economies.***

Keywords: Personal AI Assistants, Generation Z, Perceived Intelligence, Anthropomorphism, Trust in AI, and Continued Usage Intention.

I. INTRODUCTION

Artificial Intelligence (AI) has emerged as a disruptive technology in numerous industries, transforming the manner in which individuals utilize digital technologies in everyday life. Personal AI Assistants (PAIAs), such as Apple's Siri, Amazon's Alexa, Google Assistant, and ChatGPT, are a few of its most prevalent applications. Due to innovation in machine learning and natural language processing, these devices have evolved from basic voice-command interfaces to sophisticated, adaptive agents that are able to communicate in a customized and context-sensitive way (Troshani et al., 2021).

This development is particularly pronounced in Generation Z, who were born between 1997 and 2012 (Vieira et al., 2024). This generation is only familiar with digital technologies and has grown up immersed in intelligent devices, internet connectivity, and algorithm-based platforms. Artificial intelligence is not perceived by this generation as something new but as a natural and unobtrusive extension of their daily digital lives. Empirical research suggests that more than 90 percent of Gen Z users engage with several AI-driven tools weekly, reflecting normalized dependence on smart digital agents (Bunea et al., 2024).

Although classic adoption paradigms like the Technology Acceptance Model (TAM) focus on perceived usefulness and ease of use, these are not sufficient to account for Gen Z's extended interaction with AI. For natives of the internet, extended engagement comes to be shaped by more profound psychological processes, namely perceived intelligence, that is, the capacity of the AI to reason, learn, and adjust, and anthropomorphism, how much AI systems are given human-like qualities. These traits are observed to greatly affect trust, a key mediator of influencing whether users sustain interaction in the long run (Dewalska-Opitek et al., 2024; Troshani et al., 2021).

However, trust in AI is a multi-dimensional construct. It goes beyond technical reliability to include ethical congruence, transparency, and regard for autonomy and privacy, particularly pressing issues for Gen Z consumers. In contrast to its prominence, trust has typically been treated as a static consequence as opposed to a dynamic psychological process bridging user perceptions and behavioral intentions. This discrepancy is even more emphasized by the scarcity of empirical research based in high-growth, digitally emerging economies such as India, where Gen Z's behavior on AI remains unresearched (Bunea et al., 2024).

To address these gaps, the present study aims to:

1) Investigate the impact of perceived intelligence and anthropomorphism on trust in AI.
2) Explore the mediating role of trust in predicting Gen Z users' continued intention to use personal AI assistants.

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These research objectives are based on the Stimulus Organism Response (S-O-R) model, where it is hypothesized that external stimuli, e.g., users' perceptions of AI characteristics, drive internal psychological states, e.g., trust, which in turn determine behavioral responses, e.g., future usage. Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart PLS version 4.1.1.2 is used to test this conceptual model for validity. PLS-SEM is a statistical method well adapted to examining intricate relationships between latent constructs and mediation effects.

The organization of the paper is as follows. Section 2 discusses the literature and generates the hypotheses for the study. Section 3 describes the methodology, that is, sampling strategy, scale development, and analytical procedures. Section 4 discusses the empirical findings and important statistical results. Section 5 discusses theoretical and practical contributions. Section 6 presents major conclusions, and Section 7 outlines study limitations and suggests avenues for future research.

II. THEORETICAL FRAMEWORK AND HYPOTHESIS FORMULATION

A. Conceptual Framework

This research is grounded on the Stimulus Organism Response (S-O-R) paradigm, as initially postulated by A. Mehrabian, (1974), that describes how external inputs drive internal psychological processes that end up affecting behavioral responses. In this setup, perceived intelligence and anthropomorphism serve as the external stimuli, indicating users' cognitive and social judgments of AI systems. They impact the internal organismic state, defined herein as trust in AI, as a mediating variable between system perceptions and continued intention to use the technology on the part of users. The S-O-R framework allows for the inclusion of both rational and affective aspects of user experience, placing trust squarely as a central mechanism driving long-term interaction. In contrast to more mainstream technology acceptance models like TAM or UTAUT, the S-O-R model presents a more stratified view of the long-term use of AI technologies (Bunea et al., 2024; Troshani et al., 2021; Waytz et al., 2014).

B. Perceived Intelligence and Anthropomorphism

Perceived intelligence is a user's judgment of the ability of an AI system to comprehend, learn from, and adjust to contextual information. Perceived intelligence determines the user's perception of the system's competence and plays a vital part in establishing trust. When AI demonstrates intelligent behavior i.e., providing precise answers, being contextually aware, and learning with time, users tend to perceive it as reliable and competent (Glikson & Woolley, 2020; Troshani et al., 2021).Perceived anthropomorphism, on the other hand, refers to the observation of human characteristics in AI systems, such as voice, personality, or emotional sensitivity. Such human-like cues evoke feelings of social presence and emotional connection, which have the potential to increase users' faith in AI (Kim & Sundar, 2012; Nass & Moon, 2000; Waytz et al., 2014). Both of these constructs together reduce uncertainty and psychological distance between human beings and machines, hence paving the way for the development of trust. Previous research confirms that AI systems that are both cognitively able and socially appealing are more likely to gain user trust (Bunea et al., 2024; Chiragkumar B. Rathod, 2025). On this basis, the following hypotheses are formulated:

H1: Perceived intelligence (PI) has a significant effect on trust in AI.

H2: Perceived anthropomorphism (PA) exerts a strong influence on trust in AI

C. Trust in AI and Continued Usage Intention

Trust refers to the extent to which consumers are ready to rely on an AI system to accomplish tasks or make choices, particularly where there is uncertainty or risk (Glikson & Woolley, 2020). The trust is influenced by beliefs regarding the system's reliability, transparency, and ethical operation. In human-AI interactions, trust serves as a crucial mediating factor, connecting users' evaluations of system attributes to their behavioral intentions (Chancey et al., 2015). Greater trust is linked to longer-term engagement, as users are more inclined to trust the AI for their future interactions beyond the initial experience (Bunea et al., 2024). For instance, trust in AI chatbots in educational settings has been reported to mix elements of interpersonal trust with technological reliability confidence (Lotfalian Saremi & Bayrak, 2021). The same is true in mobile app use where sustained use is motivated by functional benefits, pleasure, user satisfaction, and trust (Choi et al., 2019).

Recent research highlights trust as an important psychological process linking user experience—like perceived intelligence and anthropomorphism, to sustained behavioral involvement (Epley et al., 2007; Waytz et al., 2014). When AI systems are perceived as both competent and socially human-like, users are more likely to form trust, and this will promote continued interaction. In addition, trust not only influences users' continued usage intentions directly but also serves as an intermediary that translates cognitive and affective perceptions into continued loyalty and affective commitment (Troshani et al., 2021).

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Perceived intelligence, anthropomorphism, and self-extension significantly influence the sustained use of personal AI assistants, with trust in AI serving as a full mediator in the relationship between anthropomorphism and continued adoption (Moussawi et al., 2023). Based on the above, the following hypotheses are formulated:

H3: Perceived intelligence (PI) has a significant impact on continued usage intention (*CUAI).*
H4: Perceived anthropomorphism (PA) has a significant impact on continued usage intention (*CUAI).*
H5: Trust in AI (TAI) significantly influences continued usage intention (*CUAI).*
H6: Trust in AI (TAI) acts as a mediator between perceived intelligence and continued usage intention (*CUAI).*
H7: Trust in AI (TAI) acts as a mediator between perceived anthropomorphism and continued usage intention (*CUAI).*

The aforementioned relationships between these constructs are depicted in the conceptual model shown in Figure 1.

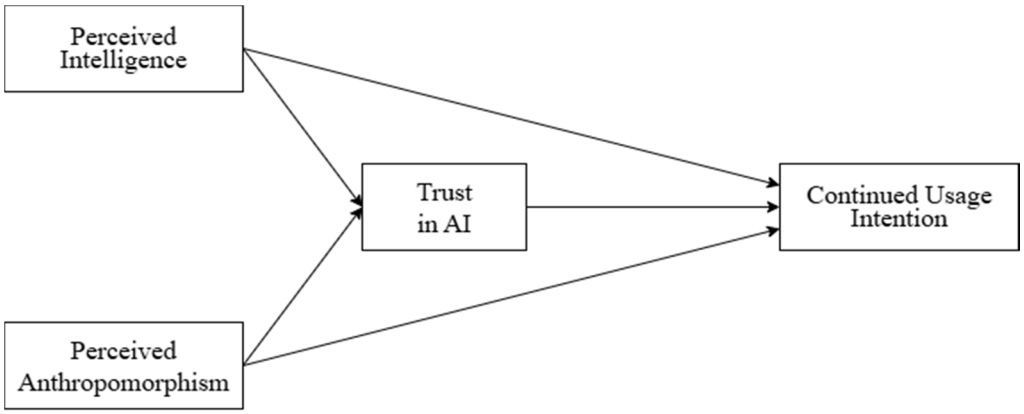

Figure 1: Conceptual Model

III. METHODOLOGY

A. *Research Design*

The current research involves a quantitative, cross-sectional design to test the hypothesized relationships among perceived intelligence, perceived anthropomorphism, trust in AI, and the intention to keep using personal AI assistants. The conceptual model is derived from the Stimulus Organism Response framework and tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of Smart PLS software version 4.1.1.2. This approach is especially useful for theory development in new fields, as it facilitates the analysis of intricate models with mediation and latent variables (Sarstedt & Cheah, 2019).

B. *Measurement Instrument*

In order to capture the latent constructs of the model proposed, a structured questionnaire was constructed using known scales from previous research and all items are on a 5-point Likert scale. Perceived Anthropomorphism and Perceived Intelligence were captured via items from (Moussawi & Koufaris, 2019), which recorded users' perceptions of human-like characteristics and mental abilities of AI assistants. Trust in AI was measured by five items from (Glikson & Woolley, 2020) that test users' faith in the assistant's fairness and dependability. Continued Usage Intention was measured with three items from (Bhattacherjee, 2001), that test users' intention to continue using the assistant. Expert review ensured content validity, and a pilot test involving 60 users validated item clarity and reliability before large-scale data collection.

C. *Sampling and Data Collection*

The study targeted active users of personal AI assistants such as ChatGPT, Alexa, Siri, and Google Assistant. A non-probability purposive sampling technique was adopted to ensure the recruitment of relevant participants who meet specific inclusion criteria. To qualify for participation, respondents had to: (1) provide informed consent to participate in the study and agree to data confidentiality, (2) confirm that they had used a personal AI assistant in the past 30 days for tasks such as asking questions, managing schedules, or generating content, and (3) self-identify as belonging to Generation Z (born between 1997 and 2012). These criteria ensured alignment with the study's focus on Generation Z's trust in and continued use of AI assistants. Data were collected using an online survey distributed through email, social media platforms, and online communities. After applying screening filters based on the inclusion criteria, a total of 131 valid responses were retained for analysis.

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D. Data Analysis Technique

Data analysis was done with SmartPLS version 4.1.1.2, a commonly used software application for Partial Least Squares Structural Equation Modeling (PLS-SEM). A two-stage analytical process was adopted. In the first step, measurement model testing was done to determine reliability and validity. Internal consistency was examined by using Cronbach's Alpha and Composite Reliability (CR), while convergent validity was gauged through Average Variance Extracted (AVE). Discriminant validity was assessed based on the Heterotrait–Monotrait Ratio (HTMT). During the second step, structural model fit was checked to verify path coefficients, significance tests (t-values and p-values), and explanation degree (R^2). Hypothesis significance was tested using bootstrapping with 5,000 resamples, and further measures such as effect size (f^2) and predictive relevance (Q^2) were noted. Mediation analysis was conducted to examine the indirect effects between constructs (Sarstedt et al., 2021).

Apart from inferential analysis, descriptive statistics were employed to profile the respondents and assess the distribution of the important constructs. The final sample (N = 131) included 52 females and 79 males. In terms of education, 103 participants were seeking undergraduate degrees, whereas 28 had already graduated. In terms of usage, ChatGPT was the most frequently used AI assistant (45 participants), followed by Siri (35), Google Assistant (32), and Alexa (19).

Descriptive analysis of the latent variables indicated that the mean value of perceived intelligence (PIT) was 19.25 (SD = 2.98), and perceived anthropomorphism (PAT) was 19.97 (SD = 4.89). Trust in AI (TAIT) averaged 18.02 (SD = 3.73), and continued usage intention (CUAIT) averaged 11.54 (SD = 2.44). Skewness and kurtosis for all constructs were within suitable limits, thus, no serious normality assumption violations. The descriptive findings aided in establishing an initial perception of users' attitudes and behaviors to form the basis for structural equation modeling hypothesis testing.

IV. RESULTS

A. Measurement Model Evaluation

In order to determine the validity and reliability of reflective constructs, outer loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were calculated. The findings are presented in Table 1.

The majority of the items proved to have good indicator reliability, with outer loadings above 0.70. Nevertheless, two items belonging to the Perceived Intelligence construct, PI2 (0.484) and PI1 (0.625), were below the acceptable value, suggesting a possible reliability issue. Likewise, PA4 (0.693) was slightly low but still within an acceptable range. For internal consistency, Cronbach's Alpha and Composite Reliability (CR) measures for CUAI, PA, and TAI were each well above the recommended figures of 0.70 and 0.80, respectively, confirming strong reliability. The PI construct revealed a borderline low Cronbach's Alpha (0.699), cautioning against interpretation, but its CR figure of 0.802 was within acceptable limits. Convergent validity was established for CUAI, PA, and TAI since their Average Variance Extracted (AVE) was over 0.50. However, PI failed to meet the AVE standard (0.453), suggesting that the scale needs to be improved by revisiting or eliminating poorly performing items like PI2. These measurement model assessment practices are congruent with specifications provided by Leguina (2015), who underlined the significance of loading thresholds, reliability measures, and convergent validity as initial steps in Partial Least Squares Structural Equation Modeling (PLS-SEM).

Table 1: Outer Loadings, Reliability, and Convergent Validity of Constructs

Construct	Item Code	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	AVE
Continued Usage of AI (CUAI)	CUAI1	0.898	0.841	0.904	0.76
	CUAI2	0.896			
	CUAI3	0.819			
Perceived Anthropomorphism (PA)	PA1	0.745	0.851	0.89	0.574
	PA2	0.783			
	PA3	0.812			
	PA4	0.693			
	PA5	0.714			
	PA6	0.793			

Perceived Intelligence (PI)	PI1	0.625	0.699	0.802	0.453
	PI2	0.484			
	PI3	0.744			
	PI4	0.728			
	PI5	0.746			
Trust in AI (TAI)	TAI1	0.751	0.846	0.891	0.62
	TAI2	0.81			
	TAI3	0.801			
	TAI4	0.782			
	TAI5	0.791			

B. Structural Model Evaluation

The structural model was assessed to examine the postulated direct associations among the latent constructs. Path coefficients, t-values, and p-values were determined through a bootstrapping analysis with 5,000 subsamples, as suggested by F. Hair Jr et al. (2014) and Leguina, (2015). The standardized regression weights and significance levels are given in Table 2.

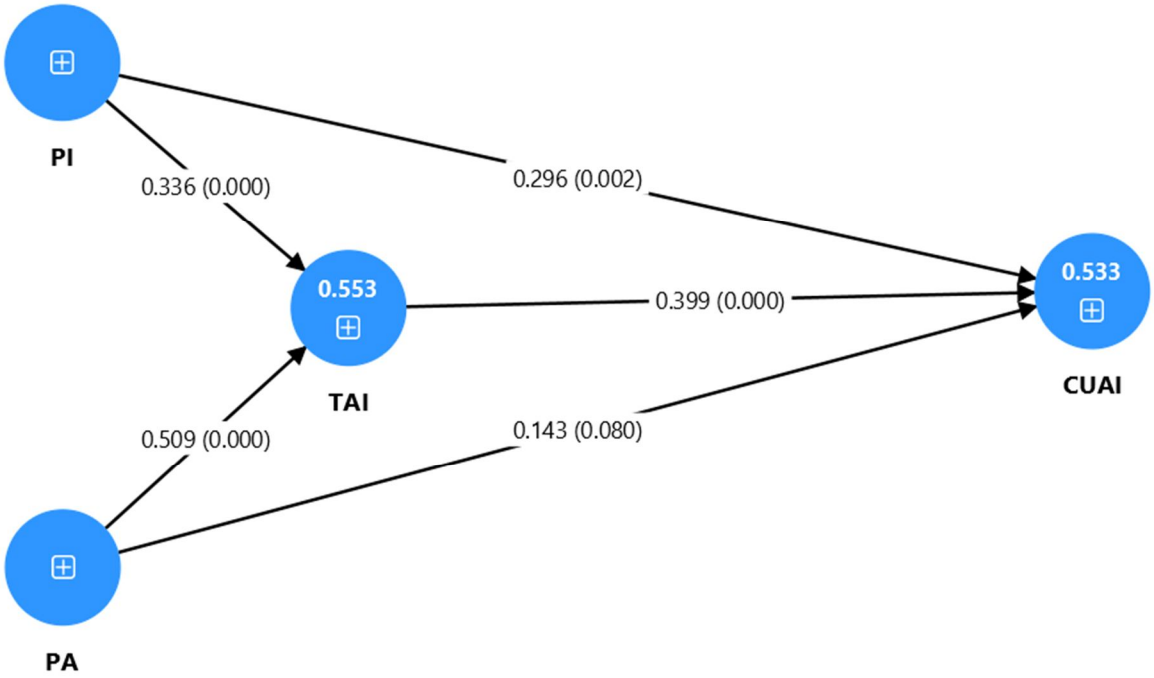

Fig 2: Structural Equation Model

Most of the hypothesized hypotheses were supported by the results provided. Perceived Intelligence positively affected both Trust in AI (β = 0.336, p = 0.000) and Continued Usage Intention (β = 0.296, p = 0.002), supporting H1 and H3. Perceived Anthropomorphism also positively and significantly influenced Trust in AI (β = 0.509, p = 0.000), supporting H2. Moreover, Trust in AI played an important role in driving Continued Usage Intention (β = 0.399, p = 0.000), supporting H5. Yet, the direct influence of Perceived Anthropomorphism on Continued Usage Intention was not significant (β = 0.143, p = 0.080), prompting the non-support of H4. These results emphasize the central role of Trust in AI in compelling long-term commitment and behavioral intention toward intelligent systems. Based on F. Hair Jr et al. (2014), determining the size and importance of structural paths by bootstrapping is essential in the validation of the predictive relationships of the PLS-SEM framework . The employment of standardized β values and p-value interpretation in this research adheres to the best practices recommended for testing model hypotheses in structural equation modeling (Sarstedt & Cheah, 2019).

Table 2: Direct Hypotheses Testing

Hypothesis	Path	β-value	t-value	p-value	Result
H1	PI → TAI	0.336	4.069	0.000	Supported
H2	PA → TAI	0.509	6.178	0.000	Supported
H3	PI → CUAI	0.296	3.141	0.002	Supported
H4	PA → CUAI	0.143	1.753	0.080	Not Supported
H5	TAI → CUAI	0.399	3.498	0.000	Supported

C. Mediation Analysis

Mediation analysis was used to verify H6 and H7 by testing the direct indirect effects of Perceived Intelligence and Perceived Anthropomorphism on Continued Usage Intention via Trust in AI. Both indirect routes were statistically significant: PA → TAI → CUAI (β = 0.203, t = 2.805, p = 0.005) and PI → TAI → CUAI (β = 0.134, t = 2.721, p = 0.007), reinforcing the mediating effect of Trust in AI. For H6, the direct path from Perceived Intelligence to Continued Usage Intention was still significant, reflecting partial mediation. For H7, the direct path from perceived anthropomorphism to Continued Usage Intention was not significant, reflecting full mediation. This is consistent with PLS-SEM mediation testing protocols suggested by Sarstedt et al. (2021), who highlight the importance of examining both direct and indirect paths via bootstrapping procedures. These results validate that Trust in AI is an influential mechanism that directs users' cognitive and social impressions of AI towards ongoing engagement behavior.

Table 3: Mediation Analysis – Specific Indirect and Total Effects

Hypothesis	Mediation Path	Specific Indirect Effect (β)	t-value	p-value	Total Effect (β)	Mediation Type
H7	PA→ TAI → CUAI	0.203	2.805	0.005	0.346	Full mediation
H6	PI → TAI → CUAI	0.134	2.721	0.007	0.429	Partial mediation

D. Predictive Relevance and Model Fit

The explanatory and predictive capacity of the model was evaluated employing the coefficient of determination (R^2), predictive relevance (Q^2), and effect size (f^2). The values of R^2 reveal that the model accounts for 53.3% of the variance in Continued Usage Intention (CUAI) and 55.3% of the variance in Trust in AI (TAI)), which implies strong explanatory power. Q^2 values for the endogenous constructs were higher than the suggested value of 0.35 (CUAI = 0.426; TAI = 0.527), ensuring the presence of strong predictive relevance. The results of effect size (f^2) indicate that PA → TAI is a large effect (f^2 = 0.418), whereas PI → TAI and TAI → CUAI are medium effects (f^2 = 0.181 and 0.152, respectively). The other paths, such as PI → CUAI and PA → CUAI, show small effect sizes. On the whole, the model shows excellent fit and significant predictive power in explaining behavioral intention to keep using AI (Sarstedt et al., 2021).

Table 4: Predictive Relevance and Effect Sizes

Endogenous Construct	R^2	Q^2 Predict	RMSE	MAE	Predictor Path	f^2	Effect Size
CUAI	0.533	0.426	0.784	0.579	PA → CUAI	0.022	*S*
					PI → CUAI	0.114	*S–M*
					TAI → CUAI	0.152	*M*
TAI	0.553	0.527	0.712	0.539	PA → TAI	0.418	*L*
					PI → TAI	0.181	*M*

Note: S= Small, M= Medium and L= Large

V. DISCUSSIONS

The findings support the expectation that perceived intelligence and perceived anthropomorphism have a significant impact on trust in AI, supporting extant theoretical connections among cognitive and social perception and trust in intelligent agents. Moussawi & Koufaris (2019) created confirmed scales demonstrating that customers perceive intelligent and human-like capabilities to be primary antecedents of trust in personal intelligent agents. Also, Song et al. (2024) established that both perceived intelligence and service robot anthropomorphism positively predicted hotel guests' intention to continue interacting with them through utilitarian and hedonic values. This finding is consistent with the general literature implying that users' trust results from perceptions of intelligence and human-likeness of the system (Kim & Sundar, 2012; Waytz et al., 2014). Research conducted by Chiragkumar B. Rathod (2025) and Glikson & Woolley (2020) also supports further the significance of such perceptions, especially among Gen Z users who anticipate emotionally intelligent and socially capable interactions with AI systems.

In our research, perceived intelligence not only indirectly impacts continued use through trust but also directly has a positive effect. This outcome further substantiates Lam (2025) prediction that users will continue to use AI systems because they view them as capable and useful. The same results were reported by Alanzi et al. (2023), who concluded that users are more likely to use AI virtual assistants when they see them as psychologically competent and helpful. On the other hand, the direct effect between perceived anthropomorphism and sustained usage was not significant; its entire impact works through trust, i.e., anthropomorphic signs have influence only if they lead to trust. This aligns with Bartneck et al., (2009) knowledge that although users react to social signals, such reactions amount to behavior only through psychological abstractions such as trust. Dewalska-Opitek et al. (2024) came to the same conclusion within their Gen Z research where emotional responses towards AI anthropomorphism heavily affected trust but not intent for direct usage.

More generally, trust in AI surfaces as an overarching mediator that converts perceptions of intelligence and human-like qualities into ongoing usage intention. The explanatory power of the model ($R^2 = 0.533$ for ongoing usage intention) emphasizes its utility. Design-wise, these results suggest that it is essential to tap into both competence signals like accuracy of performance and social signals like empathetic communication, but these attributes must systematically build trust in order to successfully sustain long-term involvement.

VI. IMPLICATIONS

A. *Theoretical Implications*

This research contributes to the theory of human–AI interaction by providing empirical support for the effects of perceived intelligence and anthropomorphism on trust in AI and future usage intention. Through the incorporation of these variables into a Stimulus–Organism–Response (S-O-R) model, this research contributes to current models of technology acceptance by showing how users' psychological reactions mediate behavioral consequences in the case of personal intelligent assistants (PIAs) (A. Mehrabian, 1974). The trust mediating function of AI provides a more complex perspective on how cognitive (perceived intelligence) and emotional (perceived anthropomorphism) signals are converted into extended interaction (Cheng et al., 2022; Choung et al., 2023). Hence, this research contributes to AI adoption research as well as consumer–technology relationships in general.

B. *Managerial Implications*

For AI personal assistant developers and marketers, the research provides design and communication tactics that can be put into practice. Augmenting perceptions of intelligence by providing quicker responses, contextual relevance, and learning adaptation can help establish strong trust, driving continued usage. Analogously, adding anthropomorphic signals (e.g., warm tone, supportive responses) can foster emotional connection, leading to greater engagement. Anthropomorphic attributes such as humor and voice enhance perceptions of warmth and social appeal, thereby fostering stronger emotional trust and increasing intentions to use the AI assistant (Chen & Park, 2021; Moussawi & Koufaris, 2019). These findings show the strategic value of not only developing AI systems for effective functionality but also for affective and relational attractiveness. Moreover, establishing trust should take precedence in AI communication, particularly in the deployment of features concerning the management of personal data or independent decision-making.

C. *Policy Implications*

While AI technologies become ever more a part of everyday life, policymakers and regulators of social media platforms must consider the psychological factors underlying trust and use revealed in this research.

Transparent guidelines for the fair behavior of AI, decisional transparency, and data protection can increase perceived justice and diminish distrust. Informing users, especially digital natives like Generation Z, about how AI systems process and decide can similarly build their sense of control and knowledgeable use.

VII. LIMITATIONS AND FUTURE RESEARCH

This research has several limitations despite its contribution, providing potential areas for future study. To begin with, the cross-sectional study design restricts the capacity to make causal inferences. Future research can explore using a longitudinal or experimental study design to confirm the time-sensitive effects of perception AI and trust building. The study employed a nonprobability purposive sampling approach targeting Generation Z users.

Although this is consistent with the research goal, it could limit the external validity of findings to older or less digitally active populations. Third, while this research tested trust, perceived intelligence, and anthropomorphism, it did not test other potentially explanatory variables like perceived privacy risk, AI transparency, or social influence. It would be possible for future research to include these constructs to develop a more complete model of AI adoption and user loyalty.

Lastly, the research centered on AI assistants in general, such as Siri, Alexa, and ChatGPT. Future research could investigate platform specific dynamics, cultural variations, or the influence of AI embodiment, e.g., voice only versus avatar based systems, on user attitudes. Longitudinal research could also investigate effects on trust loss or habituation over time to gain a better understanding of human AI relationships' long-term dynamics.

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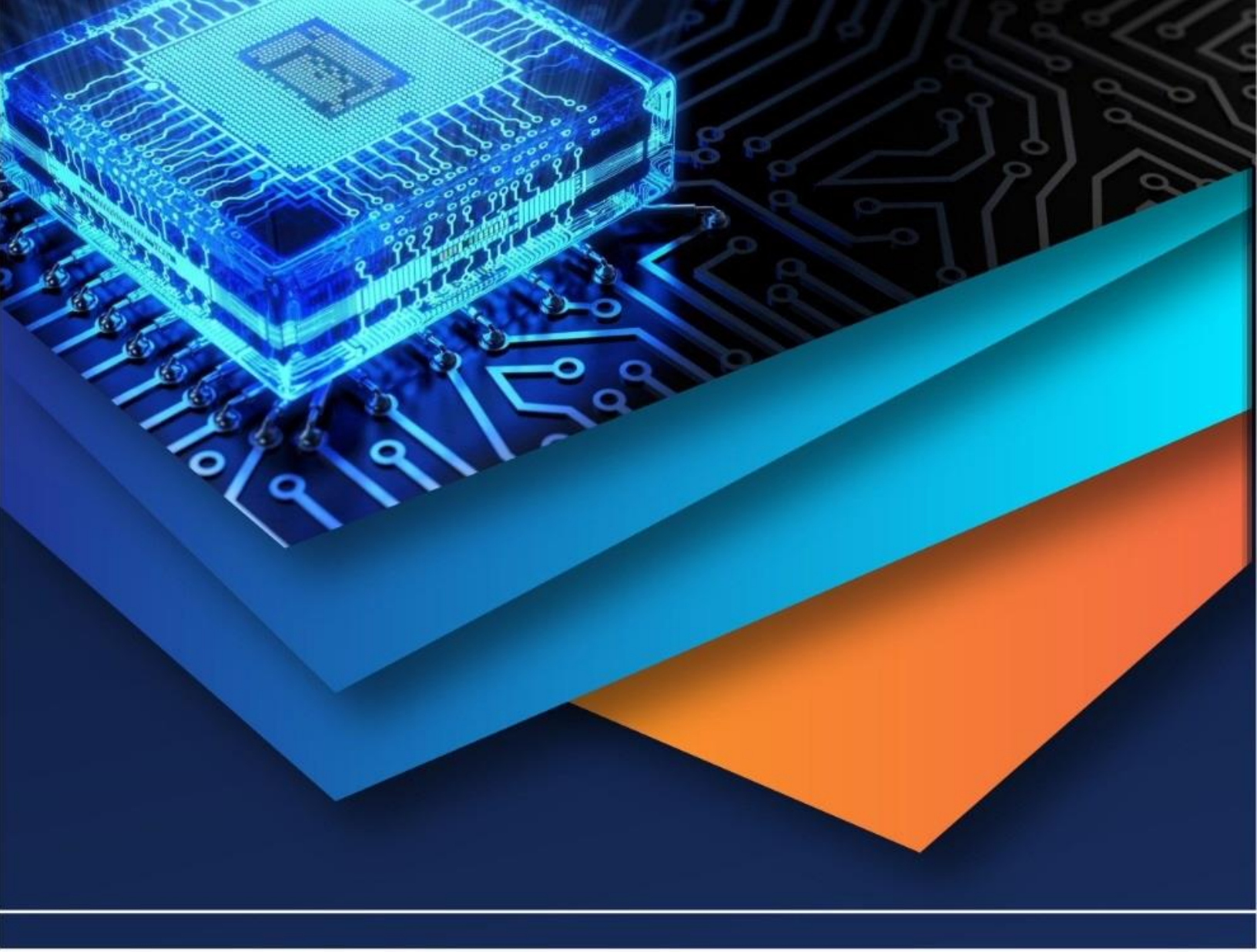

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