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Trusting the Machine: How Consumer Trust in Artificial Intelligence Shapes Future Adoption Intentions

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ABSTRACT

Although the use of artificial intelligence (AI) by consumers is growing, one of the most important factors influencing whether or not they incorporate AI into their daily lives is trust. This study examines the relationship between trust and the intentions to adopt AI-driven products in the future as well as their current use. Based on the Technology Acceptance Model (TAM) and related frameworks, we argue that perceived knowledge about AI helps to explain how trust translates into behavioral intentions and that trust functions as a fundamental mechanism influencing openness toward AI technologies. We also investigate whether this relationship is moderated by education and age. Regression results from a survey of 205 consumers provide strong support for H1: future adoption of AI is significantly predicted by trust in AI. H2 is supported by mediation analyses, which show that the trust-adoption relationship is partially mediated by perceived knowledge. Although older and less educated people descriptively reported lower trust and adoption intentions, H3, which proposed moderation by age and education, was not statistically supported. Separate trust-based segments with various behavioral patterns were also identified through cluster analysis. By highlighting trust and user knowledge as key factors in AI adoption contexts, these findings go beyond the Technology Acceptance Model/Unified Theory of Acceptance and Use of Technology (TAM/UTAUT). They also recommend that companies looking to increase AI acceptance should give top priority to improving transparency, lowering uncertainty, and informing customers about AI capabilities.

1. Introduction

Artificial intelligence (AI) technologies are becoming essential parts of daily digital interactions and are quickly changing consumer markets. AI is changing how people look for information, make decisions, and interact with digital environments through the use of virtual assistants and

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personalized recommendation systems. More than half of consumers (53%) will regularly use Generative AI applications by 2025, according to Deloitte projections. This represents a significant increase from 38% in 2024 and indicates the widespread adoption of AI-enabled services. Even with these developments, a lot of consumers are still wary of depending too much on AI because they believe that these systems are unpredictable and less reliable than human judgment. As a result, trust becomes a key factor in determining whether or not consumers accept AI technologies. According to earlier studies, even when AI tools are clearly useful or convenient, adoption may be hampered by a lack of trust. Traditional models of technology adoption, like TAM and UTAUT, emphasize how crucial perceived utility, usability, and social influence are in determining behavioral intentions [1]. They also highlight the disparities in technology adoption by demographic, with younger and better educated people generally showing more favorable views toward new digital tools [2,3]. These frameworks were created for technologies that depend much less on autonomous decision-making, though. Since AI systems frequently operate as "black boxes", adoption requires trust as a fundamental psychological requirement [4]. Perceived knowledge, or how well users think they understand AI, may also have an impact on adoption and trust [5]. People who feel informed about AI are more likely to think favorably of it, whereas people who feel ignorant might use heuristics based on uncertainty [6]. Divergent degrees of technological confidence are also correlated with demographic characteristics like age and education. In order to improve theoretical knowledge and managerial application of AI acceptance mechanisms, this study aims to clarify the ways in which trust affects AI adoption, whether perceived knowledge mediates that relationship, and whether age and education moderate it.

2. Literature Review and Hypotheses

2.1 Trust in AI and Adoption Intentions

Consumers' readiness to depend on algorithmic systems in circumstances with uncertainty or little transparency is referred to as trust in AI [7]. Customers must rely on trust as a stand-in for comprehensive knowledge because AI systems frequently make recommendations or decisions without the user explicitly understanding the internal logic [8]. Previous research in digital services and e-commerce has consistently demonstrated that trust raises users' behavioral intentions and lowers perceived risk. Similar findings have been reported in financial contexts, where trust and financial literacy significantly influence financial behavior and resilience. The mechanism is even more important in AI contexts research shows that trust significantly boosts receptiveness to AI-based personalization and adoption intentions for AI-driven applications [9]. Similarly, the effectiveness of digital outreach is often contingent on how users perceive these tailored experiences, particularly in social media environments where personalized advertising relies heavily on algorithmic trust [10, 11]. Empirical evidence from educational service settings also confirms that digital trust and brand-related perceptions significantly influence technology adoption behavior [36]. Customers can trust that AI results will meet their expectations in terms of accuracy, dependability, and ethical alignment [12]. On the other hand, despite AI's potential benefits, consumers may be deterred from implementing it if they lack trust. Therefore, we suggest: *H1: Future adoption of AI-powered products is positively correlated with consumer trust in AI*.

2.2 Perceived Knowledge as a Mediator

Consumers who are knowledgeable about AI are better able to assess algorithmic tools [13]. Being familiar tends to reduce worries about intricacy or possible mistakes and lessens anxiety when assigning work to AI systems. According to earlier research, people who are more knowledgeable and

comfortable with AI are significantly more likely to support autonomous applications [14]. The degree to which trust is translated into adoption may be influenced by perceived knowledge, or the conviction that one is aware of how AI works. People who have faith in AI might interact with it more often, progressively becoming more familiar with it and feeling more informed as a result [15]. On the other hand, more information could lessen mistrust that stems from fear. This establishes a believable mediating channel in which adoption is strengthened by knowledge and trust is fostered by knowledge. Consequently: *H2: Perceived consumer knowledge of AI acts as a mediator in the positive relationship between willingness to adopt AI products and trust in AI.*

2.3 Age and Education as Moderators

The degree to which consumers are willing to embrace new technologies varies greatly, and these variations are frequently influenced by demographic traits [16]. In general, older adults show greater skepticism toward autonomous systems and adopt digital technologies more cautiously [17]. Education also affects how well consumers comprehend algorithmic processes, assess risks, and interpret technological claims [18]. More educated users might add more evaluative criteria, while less educated people might rely more on trust heuristics [19]. These dynamics imply that the role of trust may vary based on the demographic setting. Therefore, we test: *H3: The association between willingness to adopt AI products and trust in AI is moderated by age and education attainment*.

3. Methodology

In order to achieve demographic diversity, data was collected in 2025 via an online survey that was disseminated through social media and consumer research panels. 205 responses were kept after failing attention tests were eliminated. The sample encompassed a wide range of ages, with the largest proportion falling between 18 and 24 years old, and a balanced gender distribution (55.6% female). Although there was a moderate bias toward higher education in the sample, educational attainment ranged from elementary school to graduate degrees. A structured questionnaire with scale-based items, demographic inquiries, and self-assessment tools was filled out by the respondents. The survey was completely anonymous and took about ten minutes to complete. We were able to investigate the direct impacts of trust as well as possible demographic moderation because of the wide range of ages and education backgrounds.

3.1 Measures

A five-point ordered scale was used to gauge participants' overall level of trust in AI. A parallel five-point scale measuring willingness to use more AI products was used to gauge adoption intention. A five-category scale, ranging from no knowledge to expert-level knowledge, was used to measure perceived knowledge. Although not essential to the theories, the frequency of current AI use offered behavioral context. Education was coded on a four-level ordinal scale, and age categories were translated into approximate midpoint scores. For regression analysis, all scales were regarded as interval-like. Although they were gathered, gender and work status were not used in the hypothesis test. Statistical markers are maintained constant and correlate to internal analytical references.

3.2 Analytical Approach

To evaluate the preliminary connections between trust, knowledge adoption intention, and demographics, descriptive statistics and correlation metrics were first calculated. Simple linear regression was used to test H1. H2 was investigated using mediation analysis following the Baron and Kenny method and indirect effect calculations. Regression models with interaction terms for Trust ×

Age and Trust × Education were used to test H3. To show more general behavioral patterns, cluster analysis divided respondents into three groups: low, undecided, and high-trust. Python with α=0.05 were used for the analyses. Recent studies have also applied integrated modeling approaches such as SEM–ANN to improve predictive accuracy in complex behavioral and financial systems.

4. Results

4.1 Descriptive Statistics and Correlations

According to the descriptive results, average adoption intentions were marginally positive and trust levels were moderate. The average perceived level of knowledge was low, indicating that many respondents only had a rudimentary understanding of AI. Expected correlations were found: trust had a positive correlation with perceived knowledge ($r \approx 0.30$, $p<0.001$), adoption intention ($r \approx 0.412$, $p<0.001$), and current AI usage ($r \approx 0.36$, $p<0.001$). Adoption intention and knowledge had a positive correlation ($r \approx 0.306$, $p<0.001$). Adoption intention and trust were negatively correlated with age, whereas knowledge and education had somewhat positive correlations. These trends offered a solid basis for testing hypotheses.

Hypothesis 1: Trust → Adoption Intention

Regression analysis revealed that trust accounted for 17% of the explained variance and was a strong positive predictor of adoption intention ($\beta \approx 0.42$, $p < 0.001$). Significant differences across trust levels were revealed by ANOVA ($F(2,202) = 16.78$, $p < 0.001$). The willingness to adopt AI was significantly higher among high-trust respondents (mean ~ 3.8) than among low-trust respondents (mean ~ 2.8). Additionally, trust was associated with higher current AI usage (mean 2.95 vs. 1.86). In a similar vein, cluster analysis showed rising adoption intentions among trust groups (Figure 1). H1 is fully supported.

To formally test H1, we estimated the following simple linear regression model:

$$FutureUse_i = \beta_0 + \beta_1 \cdot Trust_i + \varepsilon_i$$

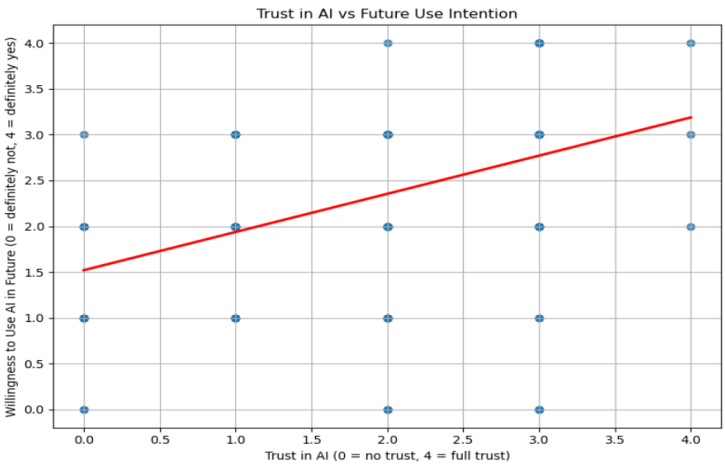

Fig. 1. Trust in AI vs future use intention

Hypothesis 2: Mediation by Knowledge

According to mediation analysis, perceived knowledge was significantly predicted by trust ($\beta = 0.30$, $p < 0.001$). Although the trust coefficient decreased from 0.417 to approximately 0.357, both knowledge and trust were still significant predictors of adoption intention. Partial mediation was confirmed by the statistical significance of the indirect effect (≈0.072). Through influencing how

knowledge is perceived, trust seems to have a direct and indirect impact on adoption (Figure 2). H2 is supported. The mediation was tested using the following set of regression equations:

Effect of trust on knowledge:

$$Knowledge_i = a_0 + a_1 \cdot Trust_i + \varepsilon_{1i}$$

Effect of trust and knowledge on adoption:

$$FutureUse_i = b_0 + b_1 \cdot Trust_i + b_2 \cdot Knowledge_i + \varepsilon_{2i}$$

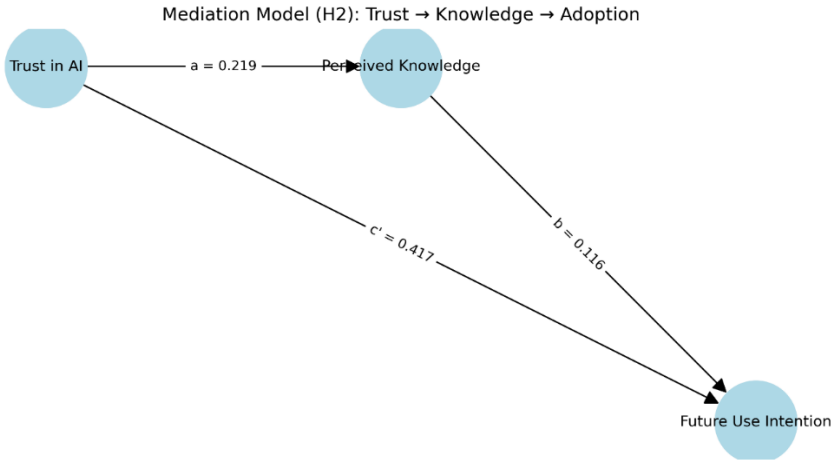

Fig. 2. Mediation by perceived knowledge

Hypothesis 3: Moderation by Age and Education

There was no obvious moderation, as evidenced by the non-significant interaction effects for Trust × Age ($\beta \approx -0.002$, $p = 0.70$) and Trust × Education ($\beta \approx 0.016$, $p = 0.857$). Although the differences were not significant, correlation comparisons revealed slightly stronger trust-intention associations among younger respondents ($r \approx 0.45$) than older respondents ($r \approx 0.33$) and among less-educated groups ($r \approx 0.48$) than more-educated groups ($r \approx 0.36$). H3, therefore, is not supported. To examine moderation effects (H3), we estimated the following model with interaction terms:

$$FutureUse_i = \gamma_0 + \gamma_1 \cdot Trust_i + \gamma_2 \cdot Moderator_i + \gamma_3 \cdot (Trust_i \times Moderator_i) + \varepsilon_i$$

5. Discussion

5.1 Key Findings

This study shows that a key psychological factor influencing consumers' receptivity to AI technologies is trust. Reiterating previous research that highlighted trust as a crucial factor in determining AI acceptance, trust consistently predicted willingness to adopt AI products. Our results add to this body of literature by demonstrating that perceived knowledge mediates this relationship to some extent, implying that trust strengthens adoption intentions by fostering familiarity and confidence. This psychological alignment suggests that when consumers feel a stronger connection to their future self and the benefits of a product, their receptivity to specific message appeals increases, much like how pride and connectedness drive ethical consumption choices [20]. Demographic trends show significant variations in baseline trust and adoption attitudes, despite the fact that age and education did not statistically moderate the trust-adoption relationship. Targeted strategies are crucial to fostering trust with older and less educated consumers, who have a tendency to express greater skepticism and fewer intentions to use AI. These findings underscore that the

successful integration of a core digital technology, much like its role in enabling sustainable urban systems, ultimately depends on addressing human factors and acceptance [21].

These results emphasize the necessity of explicitly including perceived knowledge and trust as key constructs in AI adoption contexts, which adds to theoretical models of technology acceptance. The uncertainty present in algorithmic decisions is not adequately captured by the conventional TAM and UTAUT frameworks, which place an emphasis on utility and usability. Our findings back up recommendations to include trust as a key factor influencing behavioral intention in AI contexts. The partial mediation of knowledge also implies that consumers' subjective perceptions of AI influence adoption in addition to trust. This is consistent with recent studies that highlight AI literacy as a factor in acceptance. Indeed, the ability of users to clearly articulate their understanding of AI concepts is increasingly being used as a metric for formative assessment, further highlighting the role of conceptual clarity in AI-driven environments [22]. Predictive power and conceptual completeness will be enhanced by integrating trust and knowledge into AI-specific extensions of TAM.

5.2 Managerial Implications

From a managerial perspective, companies that want to see widespread adoption of AI technologies must put a high priority on building consumer trust [23]. Transparency regarding algorithmic working, concise justifications for the recommendations made by AI systems, and easily accessible, user-friendly instructional resources are all important components of trust-building tactics [24]. Effective error-handling procedures should also be put in place by businesses; openly admitting mistakes helps keep trust from damage. Strategies that take demographics into account are crucial because older and less educated consumers might need more practical instruction, streamlined user interfaces, or hybrid human-AI support models to gain confidence. People who are younger and better educated might react more favorably to privacy and transparency and ethical guarantees [25]. Building this trust requires attention to a complex set of individual, social, and organizational determinants, a challenge well-documented in related fields like cybersecurity [26]. Businesses that exhibit dependability and transparency can greatly influence opinions in favor of AI adoption, especially considering the sizable population of consumers who are still unsure.

6. Conclusion

Trust becomes a crucial requirement for adoption as AI-driven technologies continue to spread throughout consumer settings. According to this study, perceived knowledge helps to explain this effect, and trust is a strong predictor of willingness to adopt AI technologies. Demographic factors influenced general trust and adoption attitudes, indicating that customized communication might be required for various segments, even though they did not statistically moderate the relationship. In the end, increasing technological capabilities alone is not going to be enough to increase consumer acceptance of AI; it will also be necessary to increase understanding, mitigate user concerns, and increase confidence. Organizations can close the trust gap and promote more widespread, self-assured use of AI technologies by emphasizing openness, education, and careful design.

6.1 Limitations and Future Research

The cross-sectional survey data used in this study restricts the ability to draw conclusions about causality. Although the results of mediation are consistent with theory, experimental or longitudinal designs are required to determine the temporal ordering of adoption, knowledge, and trust. The multifaceted nature of concepts like trust and knowledge may be underrepresented by single-item assessments. Objective knowledge tests or multi-item scale instruments should be used in future

research. Higher education is more prevalent in our sample, which could have an impact on adoption and general knowledge levels. Future studies could also employ advanced modeling techniques, such as the asymmetric NARDL approach used for monetary policy uncertainty [27] or LSTM models for forecasting systemic risk [28], to better capture the dynamics and non-linear relationships in AI adoption. Furthermore, the application of machine learning algorithms like XGBoost has proven effective in identifying and mitigating behavioral risks in academic settings, suggesting that similar predictive frameworks could be adapted to anticipate and address consumer trust failures [29,30]. Similarly, future studies could employ hybrid analytical approaches, such as combining Structural Equation Modeling with Artificial Neural Networks (SEM-ANN), to better evaluate complex performance metrics and decision-making patterns in supply chain and management contexts [31]. Comparable multi-criteria and hybrid evaluation frameworks have been successfully applied in higher education performance assessment under fuzzy environments [32-34]. Future research should also adopt multidisciplinary frameworks to examine how AI trust operates within complex physical and digital networks, potentially linking consumer behavior to broader systemic transitions and environmental mitigation strategies [35-37]. Investigations that are domain-specific and cross-cultural may highlight variations in settings like retail, healthcare, and finance. Other potential mediators like perceived risk or AI anxiety and moderators like personality traits or prior experience should be investigated in future studies. Additionally, longitudinal studies would shed light on how negative AI experiences affect long-term adoption trajectories and whether increased exposure to AI naturally foster trust over time.

Conflicts of Interest

The author declares no conflicts of interest.

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