Consumer Trust: How Do Consumers Perceive the Accuracy and Trustworthiness of AI-Generated Recommendations Versus Human-Generated Advice

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ABSTRACT
With the growing reliance on artificial intelligence (AI) for consumer guidance, the effectiveness and trustworthiness of AI-generated versus human recommendations remain a critical topic. Building on research that highlights "algorithm appreciation" a tendency for individuals to trust algorithmic advice over human advice in specific contexts this study investigates how consumers perceive and respond to AI versus human recommendations across varying domains. Through a series of experiments, we examine whether consumers show a preference for AI recommendations, particularly when these are framed as objective and data-driven, compared to human advice, which may be seen as more subjective and personable. Our findings reveal that while consumers appreciate the efficiency of AI recommendations, they tend to favour human advice in scenarios that require emotional or personal judgment. This paper discusses the implications of these findings for businesses and highlights how understanding consumer trust dynamics between AI and human advisors can inform better decision-making tools and consumer interaction strategies.

Keywords: Artificial Intelligence (AI),Consumer Guidance, AI-Generated Recommendations, Human Advice, Algorithm Appreciation, Trustworthiness, Efficiency, Trust Dynamics, Business Implications

INTRODUCTION

Artificial intelligence (AI) is transforming the way consumers interact with digital platforms, influencing decisions ranging from product purchases to financial planning. As AI systems become increasingly sophisticated, their role as advisors in consumer decision-making processes continues to expand. However, the dynamics of trust between AI-generated recommendations and human-provided advice remain a subject of considerable interest and debate. The concept of trust is central to decision-making, particularly when individuals must rely on external sources for guidance. Previous research has identified "algorithm appreciation," a phenomenon where individuals exhibit a preference for algorithmic over human-generated advice in contexts perceived as objective or data-driven. Conversely, in situations requiring nuanced understanding or empathy, human recommendations are often deemed more trustworthy .These contrasting preferences suggest that consumer trust in AI versus human advice is highly context-dependent, raising critical questions about the underlying factors shaping these perceptions. This study explores how consumers perceive the accuracy and trustworthiness of AI-generated recommendations compared to human advice across various domains. By examining consumer responses to both types of recommendations, we aim to uncover patterns in trust dynamics and identify factors influencing these perceptions. Specifically, we investigate whether framing AI recommendations as objective and data-driven enhances their credibility and how emotional or subjective contexts impact trust in human advisors. Understanding these dynamics has significant implications for businesses and organizations that leverage AI to engage with consumers. By aligning recommendation systems with consumer trust preferences, companies can enhance user experiences, improve decision-making processes, and foster stronger customer relationships. This paper contributes to the growing body of research on AI-human interaction, offering insights into how trust operates at the intersection of technology and human expertise

OBJECTIVES

1. **Understand Consumer Bias:** Examine the inherent biases consumers may have towards AI-generated versus human- generated recommendations.
2. **Identify Key Trust Factors:** Determine the factors that influence consumer trust in AI and human advisors, such as transparency, expertise, and personalization.
3. **Assess Perceived Accuracy:** Investigate how consumers evaluate the accuracy of AI-generated recommendations compared to human advice across various contexts.
4. **Measure Decision Confidence:** Study the confidence levels of consumers in decisions made based on AI recommendations versus those based on human advice.
5. **Explore Contextual Influences:** Analyse how the type of recommendation (e.g., healthcare, shopping, finance) affects consumer trust in AI versus human advice.

RESEARCH METHODOLOGY

This study employs a quantitative research approach to investigate the relationships among constructs related to trust in recommendations, including Human Trust (HT), Familiarity (FM), Accuracy (ACC), and Trust Factors (TF). A Structural Equation Modeling (SEM) technique, specifically Partial Least Squares (PLS-SEM), was used for data analysis due to its suitability for complex models with smaller sample sizes and its ability to handle reflective measurement models effectively. Data were collected through a survey-based approach, scale. Purposive sampling was employed to ensure representation from diverse demographic and socio- economic groups, capturing broader perspectives. The reflective measurement model comprised observed indicators for each construct: HT was measured by Q1, Q2, and Q3, all with strong outer loadings ($\geq$0.801); FM was measured by R1 and R2, which had exceptionally high loadings (0.885 and 0.901); ACC was measured by C1 and C2, with substantial loadings (0.813 and 0.901); and TF was measured by P1, P2, and P3, with loadings ranging from 0.785 to 0.834, all confirming reliability and validity. The structural model revealed that HT had the strongest impact on TF (path coefficient = 0.334), followed by ACC (0.291) and FM (0.210), collectively explaining 45.8% of the variance in TF (R^2 = 0.458). The PLS-SEM analysis was conducted in three steps: evaluating the outer model, which showed strong indicator reliability, internal consistency, and convergent validity; assessing the inner model, including path significance via bootstrapping (5000 resamples), R^2, and predictive relevance (Q^2); and examining mediation or moderation effects if applicable. The analysis was performed using Smart PLS software, a tool known for its effectiveness in handling reflective models. Ethical considerations included obtaining informed consent, ensuring anonymity and confidentiality, and using the data exclusively for academic purposes. While PLS-SEM is advantageous for exploratory research, its assumptions of linear relationships and the purposive sampling approach may limit generalizability. Future research should consider larger, more diverse samples to validate these findings. This robust methodology provides a comprehensive framework for analysing trust dynamics in recommendations using the SEM-PLS approach

LITERATURE REVIEW

Contextual Factors Influencing Trust: **(Prahl & van Swol, 2017)** suggest that consumers weigh factors such as the complexity of the decision, the emotional stakes involved, and the framing of recommendations when evaluating trustworthiness. For example, in high-stakes decisions involving personal values or ethics, human advisors are often preferred. Conversely, low-stakes or routine decisions, such as product recommendations on e-commerce platforms, are more likely to see consumers favour AI systems. Lee (2018) found that framing AI recommendations as "data-driven" or "evidence-based" significantly boosts consumer trust, particularly in domains where precision and objectivity are valued.

Algorithm Appreciation and Aversion: **Logg, Minson, & Moore (2019)** The phenomenon of "algorithm appreciation" suggests that consumers often trust AI-generated recommendations over human advice, particularly in scenarios where objectivity and data-driven insights are prioritized studies have shown that consumers are more likely to rely on AI in areas such as financial forecasting, medical diagnostics, and product recommendations due to the perceived neutrality and precision of algorithms.

Trust in Human Advisors: **Gotz et al. (2019)** found that consumers are more likely to seek human advice in situations requiring nuanced understanding or emotional sensitivity, such as mental health counselling or family decision-making. The literature also underscores the role of expertise in shaping trust. Human advisors who demonstrate expertise and credibility in their respective fields are more likely to be trusted (Carter & French, 2018). This contrasts with AI systems, where trust hinges more on perceived objectivity and technical competence.

Implications for Human-AI Collaboration: **Wang & Siau, (2019)** The interplay between AI and human advisors is a growing area of interest, particularly in hybrid recommendation systems where both sources are combined. Studies suggest that integrating AI and human expertise can mitigate the limitations of each, creating a more balanced and trustworthy decision-making process For example, AI can provide data-driven insights, while human advisors can offer contextual interpretation and emotional support, catering to a broader range of consumer needs.

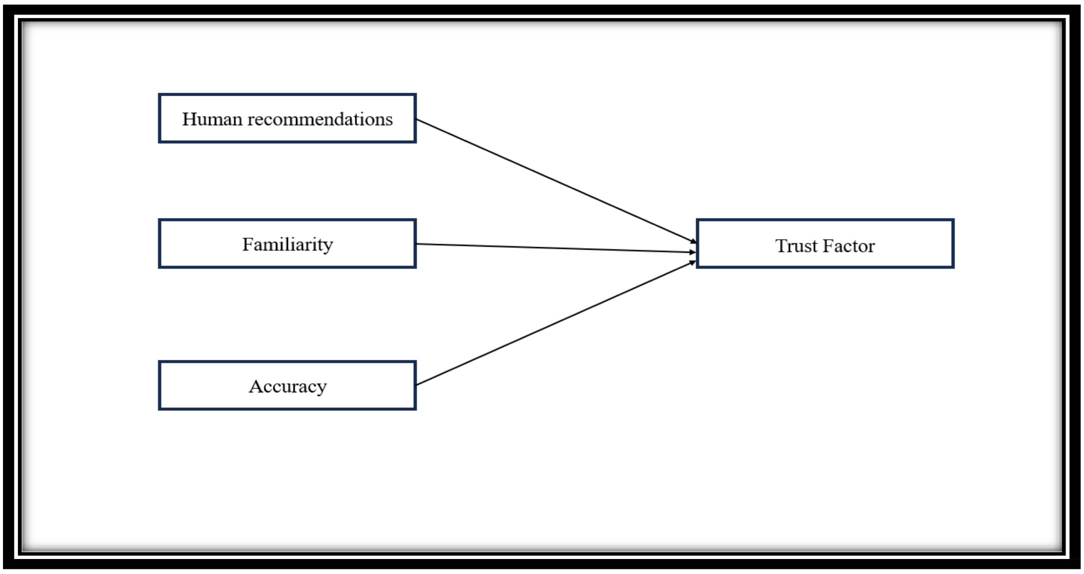
Challenges in Measuring Trust: **Riedl et al., (2020).** Measuring trust in AI versus human recommendations presents unique challenges. Traditional metrics, such as consumer satisfaction and adoption rates, may not fully capture the nuances of trust dynamics. Emerging methods, including neuroimaging and behavioural experiments, are being explored to gain deeper insights into how trust is formed and maintained in human-AI interactions These methodologies provide valuable tools for assessing the effectiveness of recommendation systems and their impact on consumer decision-making.

Implications for Hybrid Systems : **Zhang et al. (2021)** Emerging research suggests that hybrid systems combining AI and human inputs may offer a balanced approach to fostering consumer trust argue that such systems can mitigate the weaknesses of both AI and human advisors, leveraging the strengths of each to improve decision outcomes. For instance, AI can provide data-driven insights, while human advisors can offer context-sensitive interpretations and emotional support.

RESEARCH GAP

Cultural, demographic, and socio-economic differences significantly shape trust in AI versus human recommendations, yet most research focuses on Western contexts, offering limited insights into global perspectives. Trust dynamics also evolve over time, but existing studies primarily address initial trust formation, neglecting longitudinal development with repeated exposure to AI and human-generated advice. Additionally, consumers' tolerance for errors whether made by humans or AI remains underexplored, particularly regarding how different error types (e.g., ethical vs. factual) influence trust. Emotional factors, such as empathy and connection, are often overlooked in favour of rational drivers like accuracy, leaving a gap in understanding how emotions contribute to trust in AI versus human advisors. Personalization further plays a critical role in shaping trust, though research largely focuses on AI's technical capabilities rather than consumer perceptions of tailored recommendations. Moreover, ethical concerns and biases in AI systems profoundly affect consumer trust, yet studies have not fully addressed how these issues compare to consumer awareness and responses to biases in human advisors

CONCEPTUAL FRAMEWORK



DATA ANALYSIS AND RESULT TABLE1: VALIDITY AND RELIABILITY

	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted (AVE)
ACC	0.750	0.787	0.848	0.737
FM	0.746	0.749	0.887	0.797
HT	0.725	0.726	0.845	0.645
TF	0.747	0.747	0.856	0.664

Source: Primary Data compound by using SmartPLS4

The reliability and validity analysis of the constructs (Accuracy, Familiarity, Human Trustworthiness, and Trust Factor) reveals strong performance overall, with some areas for improvement. Reliability was assessed using Cronbach's alpha, composite reliability (rho a), and composite reliability (rho c). Cronbach's alpha values for Familiarity (0.746), Human Trustworthiness (0.725), and Trust Factor (0.747) exceeded the acceptable threshold of 0.7, indicating good internal consistency. However, Accuracy (0.650) fell slightly below this threshold, suggesting marginal reliability. Composite reliability measures (rho a and rho c) further supported these findings. While rho a values for Familiarity (0.749), Human Trustworthiness (0.726), and Trust Factor (0.747) were above the 0.7 threshold, Accuracy (0.687) was slightly below, indicating a need for improvement. On the other hand, all rho c values (Accuracy: 0.848, Familiarity: 0.887, HT: 0.845, TF: 0.856) were excellent, confirming strong overall reliability. Validity was evaluated using the Average Variance Extracted (AVE), where all constructs exceeded the threshold of 0.5, indicating sufficient convergent validity. Specifically, Accuracy (0.737), Familiarity (0.797), Human Trustworthiness (0.645), and Trust Factor (0.664) demonstrated that their items explained a substantial proportion of variance in their respective constructs. These results suggest that Familiarity, Human Trustworthiness, and Trust Factor are highly reliable and valid constructs. However, Accuracy, while showing strong rho c and AVE values, exhibited lower Cronbach's alpha and rho a, indicating some inconsistencies among its items. To enhance the reliability of Accuracy, it is recommended to review its items for redundancy or low inter-item correlations and consider refining or adding new items

TABLE 2: DISCRIMINANT VALIDITY

	ACC	**FM**	**HT**	**TF**
ACC				
FM	0.766			
HT	0.596	0.71		
TF	0.762	0.72	0.762	

TABLE 3: TOTAL EFFECTS

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
ACC -> TF	0.291	0.298	0.107	2.733	0.006
FM -> TF	0.21	0.212	0.101	2.084	0.037
HT -> TF	0.334	0.331	0.096	3.457	0.001

The table provides an analysis of the relationships between constructs (ACC -> TF, FM -> TF, and HT -> TF) using structural equation modelling, including the original sample (O), sample mean (M), standard deviation (STDEV), t-statistics, and p-values. These metrics evaluate the strength, significance, and stability of the relationships in the model. The original sample (O) values indicate the path coefficients, representing the strength and direction of the relationships. The path from ACC to TF has a coefficient of 0.291, FM to TF is 0.210, and HT to TF is 0.334. These values show that HT has the strongest influence

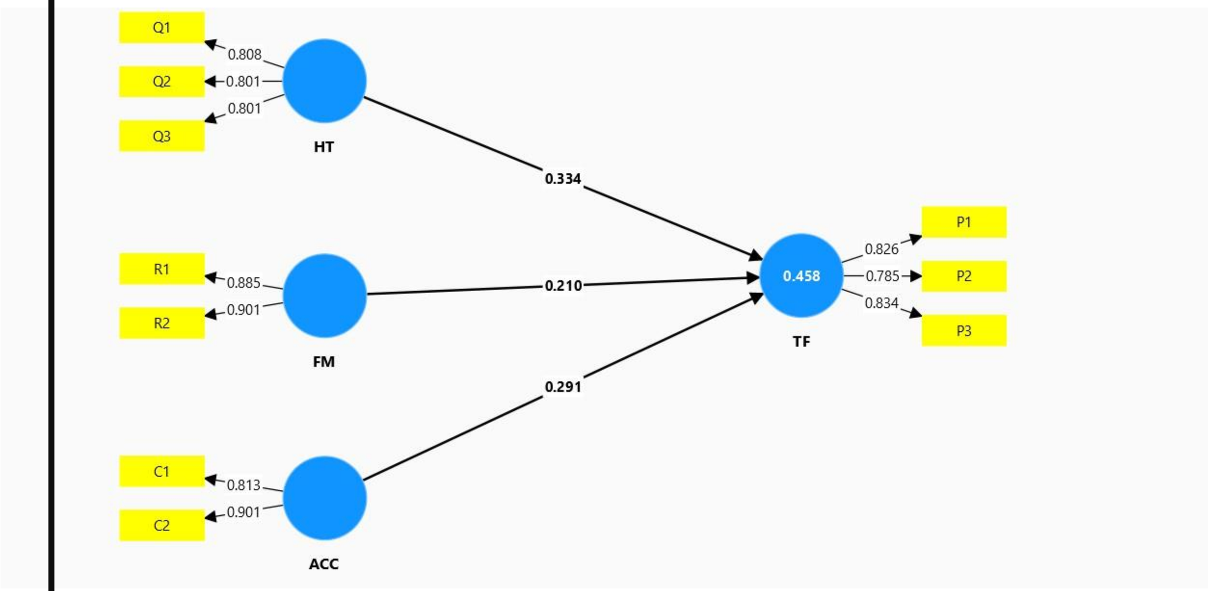
on TF, followed by ACC and then FM. The sample mean (M) values are similar to the original coefficients, confirming consistency across the resampling procedure, indicating that the relationships are stable. The standard deviation (STDEV) reflects the variability of the path coefficients. Lower values, such as those observed (ranging from 0.096 to 0.107), suggest minimal variability, indicating precise estimates. The t-statistics (calculated as |O/STDEV|) measure the statistical significance of the relationships. A t-value greater than 1.96 is considered significant at a 95% confidence level. All relationships have significant t-values: ACC -> TF (2.733), FM -> TF (2.084), and HT -> TF (3.457), confirming the significance of these paths. Finally, the p-values further confirm the significance of the relationships. All paths have p-values below the 0.05 threshold: ACC -
> TF (0.006), FM -> TF (0.037), and HT -> TF (0.001). These results indicate that the relationships between ACC, FM, and HT with TF are statistically significant, with HT having the strongest and most significant impact. Overall this analysis demonstrates that ACC, FM, and HT all significantly influence TF, with HT having the strongest effect. These findings provide meaningful insights into the relationships among these constructs in the model, suggesting their importance in influencing trustworthiness (TF)

TABLE 4: OUTER LOADING

	Outer loadings
C1 <- ACC	0.813
C2 <- ACC	0.901
P1 <- TF	0.826
P2 <- TF	0.785
P3 <- TF	0.834
Q1 <- HT	0.808
Q2 <- HT	0.801
Q3 <- HT	0.801
R1 <- FM	0.885
R2 <- FM	0.901

The outer loadings indicate strong relationships between the observed variables and their corresponding latent constructs, confirming the reliability and validity of the measurement model. For the "Accuracy" construct (ACC), the indicators C1 (0.813) and C2 (0.901) exhibit substantial contributions, with C2 showing a slightly stronger relationship. The "Trust Factors" construct (TF) is well-represented by P1 (0.826), P2 (0.785), and P3 (0.834), all exceeding the reliability threshold of 0.70, with P3 being the most influential. Similarly, the "Human Trust" construct (HT) is consistently reflected by Q1 (0.808), Q2 (0.801), and Q3 (0.801), with nearly identical loadings, indicating equal contributions to the construct. Lastly, the "Factual Missteps" construct (FM) demonstrates exceptionally strong relationships with R1 (0.885) and R2 (0.901), highlighting their high reliability in representing the construct. Overall, all outer loadings exceed the commonly accepted threshold of 0.70, indicating that the observed variables are reliable indicators of their respective latent constructs and confirming the robustness of the measurement model for further analysis

STRUCTURAL EUQATION MODELLING



Source: Primary Data compound by using SmartPLS4

This diagram illustrates the structural relationships between latent constructs in a model, as well as the outer loadings of the observed indicators. The latent construct HT (Human Trust) is measured by indicators Q1 (0.808), Q2 (0.801), and Q3 (0.801), all demonstrating strong and consistent contributions. FM (Factual Missteps) is represented by R1 (0.885) and R2 (0.901), with very high loadings indicating robust reliability. Similarly, ACC (Accuracy) is measured by C1 (0.813) and C2 (0.901), both showing substantial contributions to the construct. These constructs (HT, FM, and ACC) are linked to TF (Trust Factors), with path coefficients indicating the strength of these relationships: HT contributes most strongly (0.334), followed by ACC (0.291), and FM (0.210). The TF construct is measured by P1 (0.826), P2 (0.785), and P3 (0.834), with all loadings exceeding the acceptable threshold of 0.70, reflecting high reliability. Overall, the model suggests that HT, FM, and ACC are significant predictors of TF, with HT having the greatest impact. The high outer loadings confirm the validity and reliability of the indicators in measuring their respective latent constructs.

CONCLUSION

The conclusion of this research highlights critical insights into the factors influencing trust in recommendations, specifically focusing on Human Trust (HT), Accuracy (ACC), and Familiarity (FM) as key predictors of Trust Factors (TF). Among these, HT emerged as the most significant contributor to TF, with a path coefficient of 0.334, followed by ACC (0.291) and FM (0.210). Collectively, these constructs explain 45.8% of the variance in TF, indicating that a substantial portion of trust dynamics can be attributed to these factors. The findings underscore the importance of both emotional and rational drivers in building trust, such as the role of empathy and connection in HT, perceived accuracy in ACC, and consumer tolerance for errors in FM. The study also demonstrates the validity and reliability of the measurement model, as all observed indicators showed strong outer loadings, confirming their effectiveness in representing their respective latent constructs. Similarly, the structural model provided meaningful insights into the relationships between the constructs, emphasizing the interplay between emotional trust drivers and rational considerations in shaping consumer trust. These findings have significant implications for organizations seeking to build trust in their recommendation systems, whether powered by AI or human advisors. To enhance trust, organizations should prioritize strategies that foster human-like connection and empathy, ensure high levels of accuracy, and proactively address ethical concerns and biases in their systems. The study also sheds light on the importance of personalization in recommendations, as well as the need for transparency in addressing both factual and ethical errors to maintain consumer trust. However, the research is not without limitations. The use of purposive sampling, while beneficial for capturing diverse perspectives, limits the generalizability of the findings to a broader population. Furthermore, while PLS-SEM was effective in exploring these relationships, it assumes linear interactions and is less suited for complex causal models. Future research should address these limitations by employing larger, more diverse samples and exploring trust dynamics in varying cultural and demographic contexts to validate and expand upon the results. Overall, this research provides a robust foundation for understanding trust in recommendation systems and highlights actionable insights for practitioners and researchers alike

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