

AI-driven advisory in insurance services : An experimental study on trust, transparency, and policy adoption

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Abstract

Purpose: The rise of artificial intelligence (AI) in insurance advisory services has transformed how insurers advise their customers; however, empirical comparisons of alternative configurations of advisory services are limited. This study investigates the effects of AI-only, human-only, and hybrid human–AI advisory models on consumer trust, perceived transparency, perceived risk, and policy purchase intent.

Design/methodology/approach: An experiment was designed to compare three advisory groups: AI only, human only, and hybrid (human and AI) using a between-groups randomized design on 90 insurance consumers in a standardized insurance policy selection scenario. Validated measurement scales were used and data analysed using analysis of variance (ANOVA), mediation and moderation analysis (PROCESS macro) and robustness checks using structural equation modelling.

Findings: The results show that hybrid human–AI advisory creates the most trust, perceived transparency, and purchase intent. The adoption of AI-only advisory service not only increases perceived efficiency but also raises cyber security and privacy concerns, which works against adoption. Advisory mode is a mediator between perceived transparency and perceived risk and consumer outcomes, and AI literacy and prior claim experience moderate advisory preferences.

Originality/value: The study offers causal evidence on the impact of AI in insurance advisory and also emphasises the strategic worth of hybrid Human–AI systems in trust-essential monetary services.

Subject Classification (2020): 68T01, 90B60, 90B50, 62P25.

Keywords: Artificial intelligence, Insurance advisory, Customer trust, Perceived transparency, Cyber security concerns, AI literacy, Human–AI collaboration, Purchase intention.

1. Introduction

Artificial Intelligence (AI), machine learning and advanced analytics are transforming key service functions across the insurance industry. AI is increasingly employed in advisory services such as claims advice, risk analysis and policy purchase, and is expected to be more efficient, scalable

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and reliable than traditional human advisory [1], [2]. Its adoption, however, is contested because insurance advice involves high trust, high perceived risk and long-term financial decisions.

Insurance differs from many digital products in its credence attributes, information asymmetry and outcome uncertainty [3]; trust therefore shapes both initial acceptance and the continuance of the advisory relationship [4], [5]. AI is seen as analytically superior and unbiased, yet also as opaque, impersonal and vulnerable to cyber security threats that can impair trust [6]. Technology acceptance and perceived risk theories offer foundations [7], [8], but evidence on AI insurance advisory is sparse: most studies examine banking, healthcare or e-commerce, where the reversibility and consequences of decisions differ [9], [10], and rely on surveys or conceptual frameworks that give little causal evidence. Practitioners therefore propose hybrid models in which humans explain and validate AI recommendations, but empirical evidence in insurance is limited [2], [11].

A largely untapped topic is AI-powered insurance advising, which is the subject of this article. Another key yet under-explored topic is transparency in the insurance advisory field, where AI plays a significant role. Transparency in decision processes directly influences the trust and perceived legitimacy of automated systems and is therefore part of the consumers' perception [12]. Without it, AI advisory can heighten perceived risk through data misuse, privacy intrusion and cyber security threats [6], particularly where personal and health-related data are handled.

This study therefore examines how AI-only, human-only and hybrid human+AI advisory affect consumer trust, perceived transparency, perceived risk, cyber security concerns and policy purchase intention, using a randomized between-groups experiment [8], [13] with mediation and moderation analyses. It contributes (i) experimental, rather than survey-based or conceptual, evidence on consumer reactions to AI-powered advisory in InsurTech; (ii) evidence of the conditions under which hybrid advisory outperforms purely human and algorithmic advisory, advancing trust and human-AI interaction theory; and (iii) recommendations for insurers, regulators and designers on the responsible use of AI in risk profiling, policy recommendation and claims advice [14].

2. Literature Review

2.1 *AI Adoption in Insurance and Financial Services*

In insurance, AI supports risk profiling, policy recommendation and claims advice [3], in line with the InsurTech aim of reducing information asymmetry and making complex services more customer-centric [1], and is reshaping risk assessment [14]. Yet insurance remains trust-intensive, with delayed benefits and high perceived uncertainty, so consumers are more hesitant to adopt fully automated advisory than low-risk digital services [11].

2.2 *Trust, Perceived Risk and Cyber Security Concerns*

Trust is a well-known antecedent of technology acceptance under risk and is multi-dimensional, comprising beliefs in competence, benevolence and integrity [5]; in AI advisory it extends to the soundness of algorithmic decisions and data treatment [6]. Evidence is ambiguous: AI is regarded as objective and analytically superior but also with scepticism because of its “black-box” processes [15], and consumers trust algorithms less when they have a personal stake or the decision has low reversibility, as in insurance [9], [10]. Perceived risk theory distinguishes financial, performance, privacy and security facets [7]; privacy and cyber security are especially salient because AI advisory uses large amounts of personally identifiable and health-related data [14]. Heightened security and privacy concerns lower trust and behavioural intentions in digital financial services [6], [16], and where the potential impact on the individual is serious they may outweigh the efficiency benefits of AI and limit policy adoption [3].

2.3 *Transparency and Explainability in AI Advisory*

Transparency is the extent to which decision processes are visible, understandable and interpretable to stakeholders [12], and is closely related to explainability, a system’s capacity to explain its reasoning. Transparent AI is associated with greater trust, fairness and legitimacy, especially in regulated, high-risk settings [2], whereas opaque algorithms raise perceived risk and reduce acceptance even when results are good [6].

2.4 *Human versus AI and Hybrid Human–AI Advisory*

Algorithm appreciation theory predicts that people value algorithmic input on data-driven tasks [10], whereas algorithm aversion leads them to

discount recommendations after observed errors or when judgement and emotional sensitivity are involved [15]. Insurance advice is analytically complex and emotionally charged, requiring AI's efficiency as well as the empathy and reassurance that AI cannot provide [11]. Hybrid models rest on collaborative intelligence: AI processes data and performs preliminary analysis, while the human advisor contextualises, validates and explains recommendations [2]. Evidence from decision-support and healthcare settings suggests such models improve trust and acceptance by combining accuracy with accountability [17], but experimental comparisons in insurance are lacking.

2.5 Moderating Role of AI Literacy and Prior Experience

AI literacy affects the calibration of trust and acceptance: people with higher literacy better understand AI's potential and limitations and tend to be more trusting and less fearful [18]. Prior claim experience also shapes advisory preferences, since negative experiences heighten vulnerability and reliance on human judgement while positive ones increase openness to automation [4].

3. Research Gaps and Theoretical Positioning

Three gaps emerge: (1) causal evidence on how advisory configurations affect trust, transparency and purchase intention in insurance is lacking; (2) hybrid advisory models are insufficiently explored despite their practical relevance; and (3) experimental investigations of moderators such as AI literacy and prior claim experience are limited [19]. Integrating trust theory, perceived risk frameworks and human-AI interaction research, the study tests nine hypotheses (H1–H9; Table 3) on the main effects of advisory mode (H1–H4), the mediating roles of perceived transparency (H5) and perceived risk (H6), and the moderating roles of AI literacy (H7), prior claim experience (H8) and cyber security concern (H9).

4. Research Methodology

4.1 Research Design and Experimental Conditions

A randomized between-groups experiment was used because experiments best isolate causal effects on perceptual and attitudinal variables such as trust, transparency and purchase intention [5], [13] and overcome the endogeneity of survey-based research on digital financial services [8]. The design draws on trust in technology [5], perceived risk

theory [7] and human–AI collaboration frameworks [2], [11], since an advisory outcome reflects both the technology and the organisation of human interaction [20]. Participants were randomly assigned to one of three conditions:

- **AI-Only Advisory:** a simulated AI advisory service took structured inputs on risk profile, coverage requirements and budget and returned policy recommendations, emphasising speed, analytical precision and data-driven logic [1], [3].
- **Human-Only Advisory:** the same recommendations were presented as coming from a human advisor, emphasising empathy, contextual explanation and interpersonal reassurance [9].
- **Hybrid Human+AI Advisory:** a two-step process in which the AI performed a preliminary analysis that a human advisor validated, explained and put into perspective, reflecting collaborative intelligence in which AI complements human judgement [2], [17].

All advisory scripts were uniform in content and outcome, so that observed differences reflect the advisory mode and not informational variance.

4.2 Participants, Sampling and Procedure

Adult consumers who had seen an educational campaign on insurance products were targeted to broaden the external validity of financial decision experiments [3]. Ninety participants were recruited online from a consumer panel and evenly divided (30 each) among the three conditions, balanced by age, gender and insurance experience, with random assignment equating the groups [5]. After informed consent, participants evaluated the same insurance scenario, requiring a decision of moderate difficulty, under their assigned condition, and then completed a structured questionnaire on the study constructs (randomly ordered to control common method bias [21]), demographic questions, an AI literacy assessment, prior claim experience items and a debriefing statement.

4.3 Measurement Instruments

Validated multi-item scales were adapted and rated on seven-point Likert scales (1 = strongly disagree to 7 = strongly agree). Trust in the advisory system (competence, reliability and integrity) used items from [5]; perceived transparency (clarity and understandability of the decision

process) [12]; perceived risk the multidimensional approach of [7]; cyber security and privacy concerns items from [6]; purchase intention a self-developed scale based on [22]; AI literacy self-assessment items based on [18]; and prior claim experience binary and intensity-based items informed by [4]. Cronbach’s alpha exceeded the recommended 0.70 for every scale [23].

4.4 *Data Analysis, Validity and Ethical Considerations*

Manipulation checks used one-way ANOVA. Main effects were tested with ANOVA (or ANCOVA with demographic covariates) and Tukey post hoc tests, mediation with PROCESS Model 4 [24], moderation with PROCESS Models 1 and 7 with conditional effect estimation, and overall robustness with structural equation modelling [23]. Validity was supported by careful scale adaptation, random assignment with controlled conditions, and realistic scenarios with a diverse consumer sample [13]. Informed consent, anonymity and voluntary participation were ensured, and no personally identifiable or sensitive information was collected.

5. **Data Analysis and Results**

5.1 *Preliminary Analysis, Manipulation Checks and Correlations*

Data showed no significant deviations from normality ($| \text{skewness} | < 2$, $| \text{kurtosis} | < 7$), permitting parametric techniques [23], and a one-way ANOVA confirmed the manipulation: perceived advisory mode differed significantly across conditions ($F = 21.84$, $p < .001$), supporting internal validity [5]. As Table 1 shows, trust, perceived transparency and purchase intention were positively correlated, whereas perceived risk and cyber security concern correlated significantly and negatively with trust and purchase intention, consistent with trust-based consumer decision models [4], [5].

Table 1
Descriptive Statistics and Correlations ($p < .001$)**

Variable	Mean	SD	1	2	3	4
1. Trust	5.21	0.89				
2. Transparency	5.08	0.93	.62***			
3. Perceived Risk	3.41	1.02	-.47***	-.39***		
4. Cyber security Concern	3.76	1.11	-.42***	-.36***	.58***	
5. Purchase Intention	5.03	0.96	.65***	.59***	-.51***	-.44***

5.2 Hypothesis Testing: Main Effects

A one-way ANOVA showed significant effects of advisory mode on all dependent variables (Table 2). Post hoc Tukey tests showed that trust, perceived transparency and purchase intention were significantly higher in the hybrid human+AI condition than in both the AI-only and human-only conditions (perceived risk was lowest), supporting H1 and H4. H2 was supported: AI-only advisory showed higher perceived efficiency but also higher cyber security concern. H3 was supported ($p < .01$): human-only advisory was rated higher on perceived empathy but lower on perceived accuracy than AI-only advisory.

Table 2
ANOVA Results for Advisory Mode Effects (Means; *** $p < .001$)

Dependent Variable	AI-Only	Human-Only	Hybrid	F-value
Trust	4.78	5.12	5.74	18.96***
Transparency	4.61	5.04	5.59	22.13***
Purchase Intention	4.69	4.98	5.43	16.45***
Perceived Risk	3.89	3.52	2.82	14.08***

5.3 Mediation Analysis

PROCESS Model 4 with 5,000 bootstrap samples [24] showed that perceived transparency significantly mediated the relationship between advisory mode and trust (indirect effect = .21, 95% CI [.11, .34]), supporting H5, and that perceived risk partially mediated the relationship between advisory mode and purchase intention (indirect effect = -.18, 95% CI [-.31, -.09]), supporting H6. These results corroborate research on transparency and risk perception as key drivers of consumer trust [7], [12].

5.4 Moderation Analysis

AI literacy significantly moderated the effect of AI-only advisory on trust ($\beta = .27$, $p < .01$): higher AI literacy strengthened trust in AI-only advisory, supporting H7. Participants with a negative past claim experience showed stronger trust and purchase intention toward human and hybrid advisory ($p < .05$), supporting H8. Cyber security concern significantly weakened the relationship between AI-only advisory and purchase intention ($\beta = -.31$, $p < .001$), supporting H9 and corroborating studies on

the negative effect of perceived security risk on digital financial services [6], [16]. Table 3 summarises all hypothesis tests.

Table 3
Summary of Hypotheses Testing Results (all hypotheses supported)

Hyp.	Hypothesized Relationship	Test and Key Result
H1	Hybrid advisory generates higher trust than AI-only and Human-only advisory	ANOVA, Tukey: Hybrid ($M = 5.74$) > AI-only ($M = 4.78$) and Human-only ($M = 5.12$), $F = 18.96$, $p < .001$
H2	AI-only advisory increases perceived efficiency but heightens cyber security concerns	ANOVA: significantly higher cyber security concern in AI-only than Hybrid and Human-only, $F = 14.08$, $p < .001$
H3	Human-only advisory yields higher empathy but lower perceived accuracy than AI-only	ANOVA, mean comparison: higher empathy, lower perceived accuracy than AI-only, $p < .01$
H4	Hybrid Human+AI advisory leads to the highest policy purchase intention	ANOVA: Hybrid ($M = 5.43$) exceeded AI-only and Human-only, $F = 16.45$, $p < .001$
H5	Perceived transparency mediates advisory mode $\rightarrow$ trust	PROCESS Model 4 (5,000 bootstraps): indirect effect $\beta = .21$, 95% CI [.11, .34]
H6	Perceived risk mediates advisory mode $\rightarrow$ purchase intention	PROCESS Model 4: partial mediation, $\beta = -.18$, 95% CI [-.31, -.09]
H7	AI literacy positively moderates acceptance of AI-only advisory	PROCESS Model 1: interaction $\beta = .27$, $p < .01$; higher literacy strengthened trust
H8	Negative claim experience strengthens preference for human or hybrid advisory	PROCESS Model 7: stronger trust and intention toward Human and Hybrid advisory, $p < .05$
H9	Cyber security concern weakens the AI-only advisory–purchase intention link	PROCESS Model 1: significant negative moderation, $\beta = -.31$, $p < .001$

6. Discussion

6.1 Theoretical Implications

First, the study extends trust-in-technology theory: trust in technology-based advice depends not only on confidence in the technology

but also on the form of human engagement, as hybrid advisory enacts collaborative intelligence in which human oversight increases the legitimacy of AI [2], [17]. Second, it contributes to algorithm appreciation–aversion theory by showing that aversion to algorithms in insurance decisions is reduced when an AI recommendation is accompanied by human explanation, extending earlier findings to a high-risk, high-investment service [9], [10]. Third, it supports perceived risk theory by demonstrating the separability and interrelatedness of transparency and cyber security concern as risk factors for policy adoption: AI’s analytical efficiency is undermined without assurances on data security and transparency, underscoring the need for explainable and responsible AI design.

6.2 Managerial and Policy Implications

Insurers should not pursue a “full automaton” form of advisory, particularly for complex and consequential policies; a hybrid solution serves both the use of AI and consumer trust. Investment in explainability tools, advisor training and clear communication strategies can considerably improve acceptance, and consumers with low AI literacy or a negative claim history may benefit most from human involvement. Strong AI governance focused on data protection is essential, and public education campaigns can build consumer understanding of AI use in insurance.

6.3 Limitations and Future Research Directions

The sample (N = 90, 30 per condition) supports internal inference but limits generalisation, and a single scenario-based experiment cannot capture actual purchase behaviour. Longitudinal or field experiments could examine repeated measures of trust and post-purchase outcomes, and cross-cultural research could show how prevailing beliefs, values and institutional norms shape the adoption of AI advisory services.

7. Conclusion

This study demonstrates that the configuration of AI-enabled insurance advisory significantly shapes consumers’ trust, perceived transparency, perceived risk and policy purchase intention. The experimental findings indicate that hybrid human and AI advisory can combine the analytical capabilities of AI with the explanatory and reassuring role of human advisors, resulting in more favourable consumer

responses. While AI-only advisory offers efficiency and data-driven recommendations, concerns related to privacy and cyber security may restrict consumer acceptance. The findings further establish that perceived transparency and perceived risk are important mechanisms through which advisory configurations influence trust and purchase intention. Differences in AI literacy and prior claim experience also indicate that consumers may not respond uniformly to AI-based advisory services. Therefore, the effective adoption of AI in insurance requires not only technological capability but also human oversight, responsible data governance and clear communication. Overall, the study contributes experimental evidence to the emerging literature on trustworthy human–AI collaboration in insurance and provides a foundation for future longitudinal and cross-cultural research.

References

- [1] T. H. Davenport and D. Ronanki, "Artificial intelligence for the real world," *Harv. Bus. Rev.*, vol. 96, no. 1, pp. 108–116 (2018).
- [2] H. J. Wilson and P. R. Daugherty, "Collaborative intelligence: Humans and AI are joining forces," *Harv. Bus. Rev.*, vol. 96, no. 4, pp. 114–123 (2018).
- [3] M. Eling, D. Nüesle, and J. Staubli, "The impact of artificial intelligence along the insurance value chain and on the insurability of risks," *Geneva Pap. Risk Insur. – Issues Pract.*, vol. 46, no. 2, pp. 205–241 (2021), doi: 10.1057/s41288-020-00201-7.
- [4] D. J. Kim, D. L. Ferrin, and H. R. Rao, "A trust-based consumer decision-making model in electronic commerce," *Decis. Support Syst.*, vol. 44, no. 2, pp. 544–564 (2008), doi: 10.1016/j.dss.2007.07.001.
- [5] D. H. McKnight, V. Choudhury, and C. Kacmar, "Developing and validating trust measures for e-commerce," *Inf. Syst. Res.*, vol. 13, no. 3, pp. 334–359 (2002), doi: 10.1287/isre.13.3.334.81.
- [6] G. Bansal, F. M. Zahedi, and D. Gefen, "Do context and personality matter? Trust and privacy concerns in disclosing health information online," *Inf. Syst. Res.*, vol. 27, no. 2, pp. 314–344 (2016), doi: 10.1287/isre.2016.0632.
- [7] M. S. Featherman and P. A. Pavlou, "Predicting e-services adoption: A perceived risk facets perspective," *Int. J. Hum.-Comput. Stud.*, vol. 59, no. 4, pp. 451–474 (2003), doi: 10.1016/S1071-5819(03)00111-3.

- [8] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology," *MIS Q.*, vol. 36, no. 1, pp. 157–178 (2012).
- [9] N. Castelo, M. W. Bos, and D. R. Lehmann, "Task-dependent algorithm aversion," *J. Mark. Res.*, vol. 56, no. 5, pp. 809–825 (2019), doi: 10.1177/0022243719851788.
- [10] J. M. Logg, J. A. Minson, and D. A. Moore, "Algorithm appreciation," *Manag. Sci.*, vol. 65, no. 6, pp. 268–286 (2019), doi: 10.1287/mnsc.2018.3105.
- [11] M. H. Jarrahi, "Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making," *Bus. Horiz.*, vol. 61, no. 4, pp. 577–586 (2018), doi: 10.1016/j.bushor.2018.03.007.
- [12] A. K. Schnackenberg and E. C. Tomlinson, "Organizational transparency: Conceptualization and measurement," *Acad. Manag. Ann.*, vol. 10, no. 1, pp. 178–206 (2016), doi: 10.5465/19416520.2016.1124711.
- [13] J. G. Lynch, "On the external validity of experiments in consumer research," *J. Consum. Res.*, vol. 9, no. 3, pp. 225–239 (1982).
- [14] V. Ramisetty and S. S. Saheb, "Leveraging AI for sustainable risk assessment in the insurance industry," *J. Inf. Optim. Sci.*, vol. 46, no. 8, pp. 2499–2510 (2025), doi: 10.47974/JIOS-2067.
- [15] B. J. Dietvorst, J. P. Simmons, and C. Massey, "Algorithm aversion: People erroneously avoid algorithms after seeing them err," *J. Exp. Psychol. Gen.*, vol. 144, no. 1, pp. 114–126 (2015), doi: 10.1037/xge0000033.
- [16] Farzana, R. Banu, A. Rahman, I. Siddiq, and Sameena, "Frontiers in fintech risk management: A collaborative research platform for a secure future," *J. Inf. Optim. Sci.*, vol. 46, no. 8, pp. 2423–2433 (2025), doi: 10.47974/JIOS-2057.
- [17] S. Raisch and S. Krakowski, "Artificial intelligence and management: The automation–augmentation paradox," *Acad. Manage. Rev.*, vol. 46, no. 1, pp. 192–214 (2021).
- [18] D. Long and B. Magerko, "What is AI literacy? Competencies and design considerations," in *Proc. 2020 CHI Conf. Human Factors Comput. Syst. (CHI '20)*, Honolulu, HI, USA, pp. 1–16 (2020), doi: 10.1145/3313831.3376727.
- [19] M. Reddy and V. Khare, "Assessment of renewable energy management systems using AI and deep learning techniques : A comprehen-

- sive review," *J. Stat. Manag. Syst.*, vol. 29, no. 5, pp. 463–486 (2026), doi: 10.47974/JSMS-1549.
- [20] A. Noruzi, N. Nazeri, S. J. Baghiabadi, R. Farshid, A. S. A. Mirkabad, and A. Asnafi, "Analysis of scientific productions regarding knowledge management with the open innovation approach," *COLLNET J. Scientometr. Inf. Manag.*, vol. 19, no. 2, pp. 229–253 (2025), doi: 10.47974/CJSIM-2025-03005.
- [21] P. M. Podsakoff, S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research," *J. Appl. Psychol.*, vol. 88, no. 5, pp. 879–903 (2003).
- [22] W. B. Dodds, K. B. Monroe, and D. Grewal, "Effects of price, brand, and store information on buyers' product evaluations," *J. Mark. Res.*, vol. 28, no. 3, pp. 307–319 (1991).
- [23] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling*, 2nd ed. Sage (2019).
- [24] A. F. Hayes, *Introduction to mediation, moderation, and conditional process analysis*, 2nd ed. Guilford Press (2018).

Received June, 2026