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Research Article

Impact of Risk Perception on Predicting Trust in AI Technology Adoption: A Study in the Health Insurance Sector

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ARTICLE INFO	ABSTRACT

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Concerns regarding consumer intentions and trust have been highlighted by the quick adoption of AI in the health insurance industry. This study looks at how trust and the desire to adopt AI-based health insurance solutions are shaped by risk perception. Perceived risks, such as worries about data privacy, the accuracy of AI-driven judgments, and ethical issues may impact consumer confidence. This study investigates the relationship between these risk perceptions and elements that foster trust, including explainability, transparency, and the perceived advantages of AI applications. The relationship between risk perception, trust, and technology adoption is ascertained using a quantitative technique that involves survey data collection and statistical analysis. The results demonstrate how important trust is in allaying worries and promoting adoption of AI in health insurance. This research provides valuable perspectives on how consumers perceive and intend to interact with AI, adding to the expanding field of AI adoption studies. The findings can help insurers, legislators, and AI developers devise plans to mitigate risks, build confidence, and encourage the prudent application of AI in the health insurance industry.

Keywords: Consumer intention, perceived risk, trust, AI adoption.

1. Introduction

Artificial Intelligence (AI), a subset of Information Technology, is closely linked with automation and robotics. The Oxford Dictionary Artificial Intelligence refers to the creation of machines and computer programs that can carry out functions normally requiring human cognitive abilities. These functions include interpreting visual inputs, understanding and processing spoken language, making informed decisions, and translating between different languages. Technologies such as Machine Learning, Deep Learning, and Natural Language Processing are presently limited to specialized areas, functioning within the boundaries of their current technological abilities.

The early 21st century saw a surge in AI advancements, fuelling discussions on its transformative role across industries and society. AI has witnessed remarkable growth, driven by enhanced computational power and vast data availability (Lu et al., 2018). Cognitive tasks that were previously only performed by humans can now be performed by smart technology (Coombs et al., 2021). Numerous industries, including manufacturing, logistics, healthcare, and retail, have embraced these developments (Leone et al., 2021). The market for AI software is expanding quickly; as of 2020, it will have grown at a global rate of 38% annually and generated $22 billion in sales (Tractica, 2019). AI is being heralded as a game-changing innovation in the travel and tourism industry (Ivanov & Webster, 2019), bringing about digital transformation that rethinks value creation, organizational models, and strategic approaches (Murphy et al., 2017). In the upcoming years, its revolutionary impact on industry dynamics and consumer behaviour is expected to increase dramatically (Brynjolfsson & McAfee, 2014). Within the health insurance sector, AI-driven technology is ushering in a paradigm shift. As digital solutions permeate every aspect of modern life, the healthcare industry is leveraging AI to enhance operational efficiency and value delivery. Health insurers are actively adopting AI tools, accelerating processes such as customer onboarding, risk assessment, decision-making, and claims processing, all while reducing costs. Despite AI's ability to streamline operations and improve efficiency, human oversight remains essential for certain critical functions. Today, over 95% of health insurance policies are digitally issued, and major private insurers report substantial improvements in claims processing speed through AI-enabled automation. According to a 2023 survey by The Times of India, approximately 65% of cashless claim evaluations now rely on AI tools. In this rapidly evolving landscape, the

implementation of AI within the health insurance sector has primarily focused on issues related to perceived risks and the establishment of trust. As the industry embraces AI's transformative potential, understanding public and organizational perceptions of its risks and the role trust plays in this equation is crucial.
India's healthcare ecosystem is uniquely complex, grappling with challenges related to accessibility, affordability, and infrastructure. While the nation's health insurance sector has expanded significantly, persistent hurdles remain in areas such as claims processing, risk evaluation, and trust-building. Given these challenges, studying AI's impact on health insurance across various Indian states is vital to navigating the sector's future and optimizing its potential for transformation.

2. Theoretical Background

2.1 Perceived Risks in AI usage

AI-related risks can arise at multiple stages of the application programming interface (API) system lifecycle (Cheatham et al., 2019), including planning, poor data governance, biased or non-representative training data, flawed deployment, inadequate human oversight, cybersecurity threats, and technological failures. Consumer perceptions of risk and trust are important factors in the adoption of AI since larger perceived risks result in rejection, whereas trust promotes acceptance (Yanushkevich et al., 2019). AI risks are divided into two main categories by Perry and Uuk (2019): technology security and management, which includes ethical, political, economic, and military issues. One of the most significant challenges in AI adoption is bias, which can be embedded in corporate culture, personal biases, or data selection. It is essential to address data bias when selecting training datasets, as human-labeled data can introduce unintended prejudices. Continuous monitoring is necessary to prevent bias from creeping into evolving models.
Aytekin et al. (2021) highlight that AI in marketing enhances consumer analysis and decision-making, offering significant benefits to businesses. However, as technology advances rapidly, managing associated risks becomes increasingly challenging. While AI's advantages are widely recognized, potential risks are often overlooked. This study examines how different demographic groups based on age, gender, income, and profession perceive AI risks. It also explores how individuals in various fields, such as trade, marketing, entrepreneurship, engineering, and programming, view AI risks and their impact on adoption.
AI-related risks can arise at various stages of the Application Programming Interfaces (API) system lifecycle (Cheatham et al., 2019). These risks span from the initial planning phase to data handling issues, such as poor data quality or weak governance, as well as biases in model training due to prejudicial or non-representative data. Additional concerns include incorrect deployment, inadequate cycle of human training, cybersecurity vulnerabilities, and failures within the broader technological ecosystem. Consumer perceptions of *trust* and *risk* play a crucial role in AI adoption. While trust fosters acceptance, heightened perceived risks can lead to resistance (Yanushkevich et al., 2019). Perry & Uuk (2019) categorize AI-related risks into two broad dimensions: The regulation and oversight of AI encompass a broad range of domains, including ethical considerations, legal frameworks, economic implications, military applications, political dimensions, and the safety of AI systems. The perceived risk theory, as discussed by Chen (2010), provides valuable perspectives on consumer behavior, particularly in situations marked by uncertainty or ambiguity. When faced with ambiguity, consumers seek information to increase their confidence in decision-making. Framarz et al. (2016) define perceived risk as the financial stakes involved in a transaction, while Gasawneh et al. (2022) describe it as a subjective consumer perception regarding the certainty of expected benefits, emphasizing loss and uncertainty. The relationship between perceived risk and AI adoption intentions varies across individuals and contexts. Based on this understanding, the following hypothesis is proposed:
H.1: "Perceived risks play a significant role in predicting Intentions to use AI"

2.2 Perceived Risks vs Trust

A consumer's decision to use AI technology is greatly influenced by their perception of the risks. Trust is inherently linked to user expectations when expectations rise, so does trust. Likewise, success and failure rates influence these expectations, with higher success rates fostering greater trust (Bitkina et al., 2020). In this study, perceived risks refer to how consumers interpret the potential uncertainty and negative outcomes associated with conducting transactions online. In situations where the future appears uncertain or beyond their control, individuals tend to rely heavily on trust as a key factor in their decision-making process. Trust becomes even more critical in risk-based exchanges, such as

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purchasing insurance online, where uncertainty is higher (Zarifis et al., 2021). AI's growing role in health insurance introduces new challenges, as its lack of human traits and perceived unpredictability can undermine consumer confidence (Torre et al., 2020). Psychological and social factors influence trust, with structural assurances like security measures and approval seals helping to reinforce it (McKnight & Chervany, 2001; Sha, 2009). However, heavy reliance on AI in decision-making may erode consumer trust, as AI's unpredictability, lack of transparency, and limited human oversight raise concerns over control and accountability.

To drive AI adoption, businesses and technology providers must actively mitigate perceived risks by addressing ethical concerns, ensuring transparency, and delivering exceptional user experiences. A well-managed trust-building strategy enhances consumers' willingness to embrace AI, acknowledging its transformative potential in improving healthcare and insurance services while minimizing perceived risks.

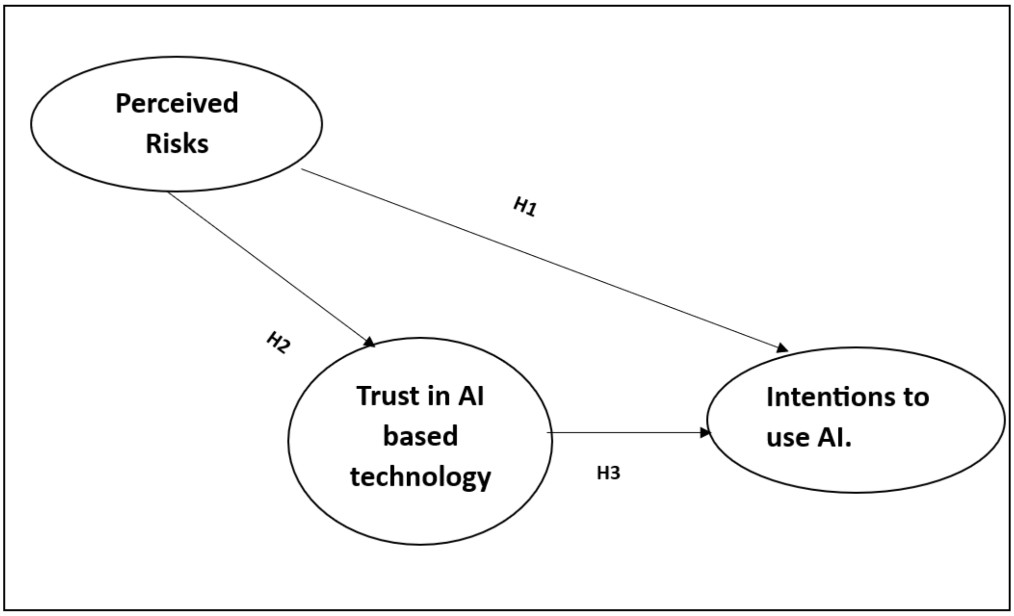
H2: Perceived risk possesses a significant relationship while building trust in AI-based technology.

2.3 Trust in AI technology

Trust in AI systems is difficult to define, as it involves complex psychological and social factors (Crockett et al., 2020). According to the Cambridge English Dictionary, trust is the belief in the reliability of someone or something. A strong ethical environment relies on trust, which can be fostered through safeguards, policies, and collaborative efforts (Ho et al., 2020). In health insurance, trust is fundamental to the relationship between insurers and policyholders, helping to address information asymmetry, where one party has more knowledge than the other. Trust also plays a vital role in data governance, empowering consumers with control over their personal data while setting clear limits on how insurers can use it for actuarial purposes, such as assessing health risks and determining premiums.

Consumers' perceptions of AI's expanding role in health insurance can significantly impact trust, sometimes leading to skepticism. The growing adoption of AI across both the front-end and back-end of supply chains introduces fresh challenges related to trust, largely because AI is often seen as unpredictable and lacking human traits. The absence of human-like characteristics, such as visual and auditory emotional expressions, may further weaken consumer trust in virtual agents (Torre et al., 2020). Trust in AI tools is a key determinant of users' willingness to adopt AI-based technology in the health insurance sector. To drive AI adoption, organizations and technology providers must actively build trust by ensuring reliability, transparency, ethical AI practices, and tangible user benefits. As confidence in AI strengthens, so does its potential to transform the health insurance industry delivering more efficient, personalized, and effective services to policyholders

H.3: "Trust in AI technology plays a significant role in predicting intentions to use AI."



Conceptual Framework (Fig 1)

3. Research Methodology and Data Collection

3.1 Sample

In order to evaluate the theoretical framework, we looked at how users of health insurance perceived, trusted, and ultimately chose to employ AI tools. Students, academics, professionals, and government workers who volunteered for the study in exchange for extra credit made up the research participants. Considering the results of this investigation and a trust-oriented consumer decision-making framework applied to health insurance users, the data revealed that individuals utilizing AI tools in this sector tend to be younger and possess higher educational qualifications compared to conventional users. These participants were also identified as frequent and engaged users of AI technologies. Over 90% of our respondents said they bought and managed health insurance policies using AI, and their average self-rated experience was 3.52 on a 5-point scale. 421 responds in all were obtained from the Jammu division in Jammu and Kashmir. A total of 374 valid responses were included in the final sample for the purposes of construct validation and hypothesis testing, following the elimination of incomplete, irrelevant, and duplicate entries.

3.2 Generation of Scales

Constructs	**Sources**
Perceived Risks	Cheatham.et.al., 2019; Mitchell, 1999; Jordan et.al., 2018.
Trust	Choudhury & Kacmar, 2002; McKnight et. al., 2011.
Intentions to use AI	Bratteli, 2018; Riikkinen et.al., 2018.

(Table 1)

4. Data Analysis and Results

To facilitate preliminary data analysis, a pilot study was conducted first. This was followed by a thorough survey that yielded 374 useful results. Both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were employed in the pilot phase to refine the assessment items and ensure construct validity and reliability. The underlying structure of the research variables was discovered with the use of EFA and Varimax rotation. In order to validate the measurement model and evaluate psychometric qualities like construct validity and reliability, CFA was then conducted using AMOS software. By comparing the average variance extracted (AVE) to the squared correlations across constructs, discriminant validity was assessed using the standards set by Fornell and Larcker (1981). After cleaning and preparing the survey data, structural equation modelling (SEM) was utilized to analyse the hypothesized relationships between variables. The study employed three separate models to test the proposed hypotheses and assess the adequacy of model fit.

4.1 Scale Assessment (EFA)

To refine the dataset, both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were employed. For simplification of variable interpretation, component analysis was conducted using quartimax rotation. During factor extraction, only those items with factor loadings above 0.50 were retained, ensuring adequate item representation. The applicability of EFA was validated through a Kaiser-Meyer-Olkin (KMO) measure exceeding 0.70 and a statistically significant Bartlett's Test of Sphericity (BTS), in line with the criteria outlined by Malhotra and Birks (2005), as illustrated in Table 1. Additionally, only those factors explaining more than 50% of the total variance were considered acceptable. The construct of Perceived Risks was found to consist of two underlying dimensions, identified as "financial risks" (PRA) and "privacy risks" (PRB). On the other hand, the constructs of "Trust" and "Intentions" emerged as unidimensional in nature.

Dimensions & Round	No. of Items	KMO	BTS	VE	Iteration	Total Factors	Deleted Items	Retained Items
Perceived Risks	11	0.823	2546.071	64.574	3	2	1	10
Trust	10	0.911	2981.985	65.916	1	1	0	10
Intentions	12	0.909	4892.535	70.607	1	1	2	10

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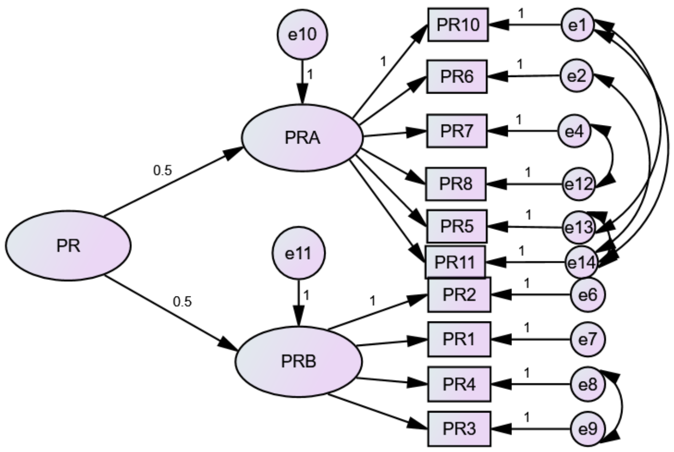
(Table 2)

Constructs	No. of Items	Factors Loading	SRW's	Cronbach Alpha Value	Composite Reliability	AVE
Perceived Risks	11	0.631-0.901	0.533-0.917	0.879	0.87	0.37
Trust	10	0.771-0.853	0.666-0.853	0.942	0.75	0.52
Intentions to use AI	12	0.740-0.913	0.700-0.947	0.961	0.81	0.41

(Table 3)

4.2 Measurement Model Analysis (CFA)

4.2.1 **Perceived Risks**: All of the items under the perceived risks construct's two dimensions showed standardized regression weights greater than 0.50, confirming the construct's validity. The Average Variance Extracted (AVE) was 0.37 and the composite reliability was 0.87. Additionally, the perceived risks dimension has a Cronbach's alpha value of 0.879, which indicates strong internal consistency (see Tables 2 and 3). With CMIN = 3.963, RMR = 0.050, CFI = 0.954, NFI = 0.943, GFI = 0.934 and RMSEA = 0.072, the model fit indices from the CFA analysis showed a strong fit (see Table 4). The confirmatory factor analysis also showed that two different dimensions financial risk and privacy risk each representing important issues impacting people, are the best way to understand perceived risks (see Fig. 2).



(Fig. 2)

4.2.2 **Trust:** The standardized regression weights of all connected items were above 0.50, confirming the construct validity for trust. The average variance extracted (AVE) was 0.52 and the composite reliability was computed to be 0.75. Additionally, the construct had a Cronbach's alpha of 0.942, indicating good internal reliability (see Table 3). According to Table 4, the fit indices (CMIN= 4.103, NFI = 0.963, RMR = 0.031, CFI = 0.972, GFI = 0.947 and RMSEA = 0.072) demonstrated that the model fit the data well. It was determined that trust is a unidimensional construct based on the measurement model analysis (see Fig. 3).

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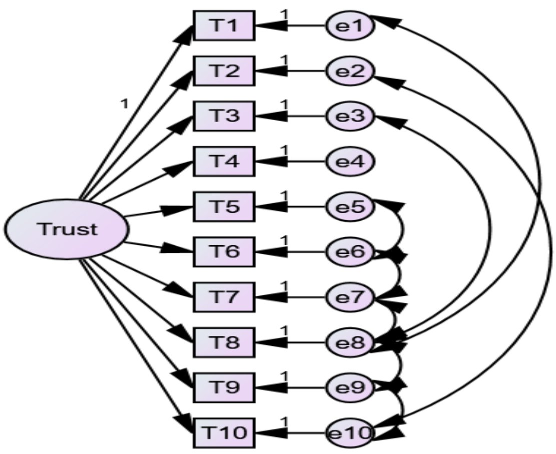
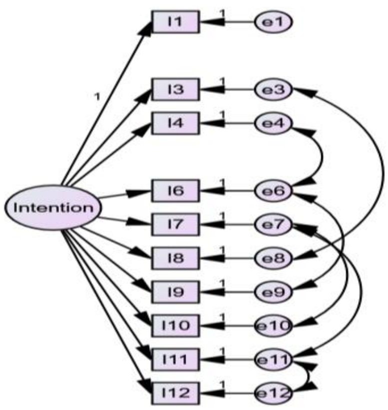


(Fig. 3)

4.2.3 **Intentions to use AI:** While every other item had standardized regression weights more than 0.50, construct validity for the intention variable was validated. The composite reliability was 0.81 and the Average Variance Extracted (AVE) was 0.41. This design had an exceptionally high Cronbach's alpha score of 0.961 (see Table 3). A good model fit was also corroborated by the model fit indices, which showed the following values (see Table 4): CMIN = 4.103, RMR = 0.031, , GFI = 0.94, NFI = 0.963, CFI = 0.972 and RMSEA = 0.072. The measurement model verified that the construct of purpose is best represented as a single-dimensional component after two items were removed (Fig. 4).



(Fig. 4)

Constructs	CMIN	RMSEA	GFI	NFI	CFI	RMR
Perceived Risks	3.963	0.078	0.934	0.943	0.954	0.050
Trust	4.103	0.072	0.947	0.963	0.972	0.031
Intentions to use AI	3.554	0.080	0.950	0.973	0.980	0.033

(Table 4)

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As both Cronbach's alpha and composite reliability scores were within acceptable threshold limits, all constructs showed good reliability and validity. In addition, discriminant validity was assessed using both the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker approach. The outcomes of these assessments are detailed in Tables 3 and 5. The AVE values for service innovation, collaborative knowledge production, and organizational performance were found to be somewhat below the suggested level, even though the majority of indicators met the normal benchmark standards.

Constructs	Perceived Risks	Trust	Intentions
Perceived Risks	(0.67)		
Trust	0.637	(0.59)	
Intentions	0.649	0.590	(0.66)

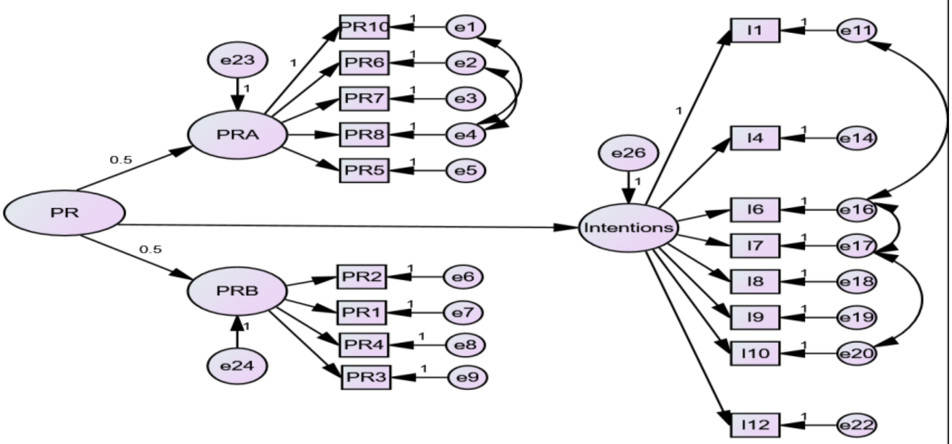
Table 6 (Discriminant Validity)

4.3 SEM Analysis/ Hypothesis testing

The data from the survey was used to test the study hypothesis for which structural equation modelling using AMOS was undertaken. The analysis was conducted using three separate models. Model 1 was used for testing the role perceived risks in predictiong Intentions to use AI; and model fit analysis. Model 2 was used to test the relationship between perceived risks in building trust towards AI the and model 3 assessed the role of trust in predicting intentions to use AI based technology

4.3.1 *H.1: "Perceived risks play a significant role in predicting Intentions to use AI"*

According to SEM results, intentions to use AI in the context of the health insurance industry are significantly correlated with perceived risks. The findings indicate a strong correlation between user intentions and perceived risks, with the β-value being 0.875 and p value being significant. This suggests that lower intents to embrace AI-based technologies are linked to higher perceived dangers. Table 5 displays the detailed model fit indices. Consumer reluctance to use AI is significantly influenced by the fundamental aspects of perceived risk, such as privacy concerns and finacial risks. Hypothesis 1 (H1) is therefore accepted.



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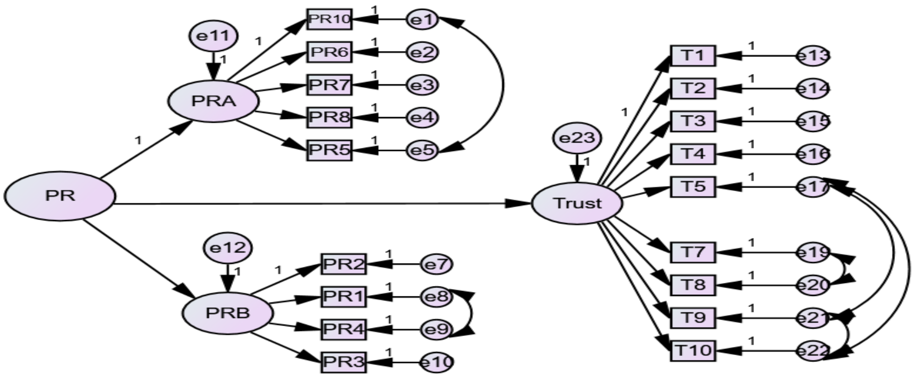
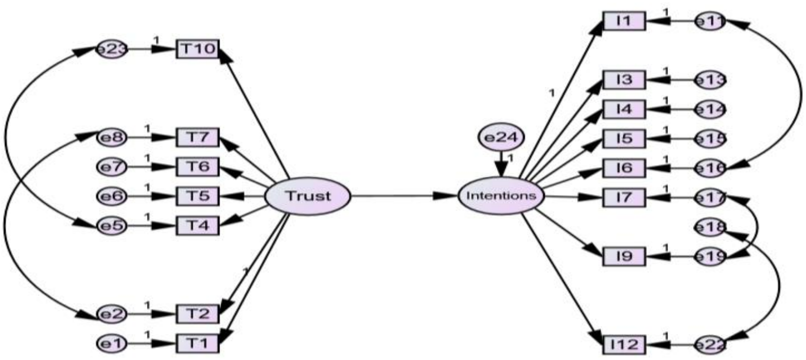
4.3.2 *H2: Perceived risk possesses a significant relationship while building trust in AI-based technology*.

SEM results show that, in the health insurance industry, perceived risk and trust in AI-based technology are significantly correlated. With a β-value of 0.984 and significant p value the results show a substantial correlation between perceived risks and trust, indicating that trust in AI-based systems decreases as perceived risks rise. Table 5 displays the detailed model fit indices. Consumer trust in AI systems is steadily declining due to key risk factors. As a result, hypothesis 2 (H2) is accepted.



4.3.3 *H.3: "Trust in AI technology plays a significant role in predicting intentions to use AI."*

According to SEM results, intentions to use AI in the context of the health insurance industry are significantly correlated with trust in AI technology. Higher levels of trust in AI greatly increase the possibility of its acceptance and usage, according to the findings, which show a strong and positive connection between trust and user intents (β-value = 0.731). Table 5 provides the detailed model fit indices. Consumer willingness to interact with AI-based systems is positively impacted by aspects of trust, such as perceived dependability, transparency, and ethical AI use. Hypothesis 3 (H3) is therefore accepted.



Relationship	SRW's	CMIN/ df	NFI	CFI	RMR	RMSEA	P Value	Result
PR → Intentions	0.875	4.599	0.903	0.922	0.041	0.078	***	Supported
PR → Trust	0.984	3.958	0.875	0.897	0.039	0.03	***	Supported
Trust → Intentions	0.917	4.216	0.718	0.762	0.049	0.061	***	Supported

(Table 5)

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5. Discussions and Implications

This study emphasizes how consumers' intentions for utilizing AI-based technologies in the health insurance industry are significantly influenced by their perceptions of risk and trust. The results provide compelling evidence in favor of the three hypotheses put forth, each of which advances our knowledge of how people evaluate and choose to use cutting-edge technologies in delicate fields like healthcare and insurance. First, the validation of H1 that perceived risks have a significant impact on the intention to use AI indicates that consumers' concerns about problems like algorithmic errors, data privacy breaches, lack of human oversight, and possible misuse of personal health information can be significant barriers to the adoption of AI. These issues are especially noticeable in the context of health insurance, when user acceptability depends on system trust and the consequences are substantial. Regardless of the effectiveness or creativity of AI technology, these perceived risks could lead to resistance and mistrust if they are not appropriately addressed.

The confirmation of H2, which states that perceived risk and trust are significantly correlated, emphasizes even more how risk perception impacts both intention and the fundamental confidence in AI systems. Customers lose faith in AI systems when they believe that these systems could violate their privacy, behave in an opaque manner, or make biased conclusions. In this situation, perceptions of security, openness, and justice are strongly related to trust. Health insurance companies and AI developers must thus utilize transparent algorithms, guarantee accountability in decision-making procedures, and communicate clearly about how AI uses user data in order to foster confidence. Organizations may create a foundation for sustained trust in AI by confronting perceived risks openly and promoting a feeling of safety and equity.

Furthermore, H3 highlights that intention to employ AI technologies is highly predicted by faith in the technology. The known function of trust as a key mediator in technology adoption models is confirmed by this research. Users are more inclined to interact with AI technology when they think these systems are competent, moral, and in their best interests. Trust serves as a psychological guarantee that the technology will operate safely and dependably, particularly in intricate settings like health insurance where customers could feel exposed. Therefore, for stakeholders looking to advance AI-based solutions, establishing and preserving confidence should be a top strategic objective.

The combined knowledge gained from this study has significant applications. Strict data privacy regulations, user-centered design principles, and effective consumer education campaigns are all necessary proactive steps that health insurance firms and legislators may take to lower perceived risks. Greater acceptability can also be achieved by implementing trust-building techniques, such as providing human-AI collaboration models, guaranteeing algorithmic transparency, and permitting user feedback methods. In the end, by addressing the psychological and emotional elements impacting consumer behavior, this research offers a road map for effectively incorporating AI technology in the health insurance industry. Recognizing and addressing the interplay between perceived risk and trust can enable stakeholders to enhance user willingness to adopt AI, thereby promoting its sustained integration within health insurance services.

Future Research and implications

The study adds a lot to the volume of information; it also has several shortcomings that may open up new research directions. The generalizability of the results may be impacted by the fact that the study's respondents are from Jammu. In order to improve generalization, it is advised that future research take into account collecting responses from various geographic locations. Future research could examine the effects of variables including age, education, digital literacy, and prior AI experience on customer attitudes and actions. Deeper insights into how trust in AI changes over time with greater exposure and familiarity may potentially be provided by longitudinal studies. Investigating the effects of particular AI application types like AI-powered claim processing, customer support chatbots, or risk profiling tools on perceptions of risk and trust would also be beneficial. Experiments evaluating the efficacy of various trust-building techniques, including explainable artificial intelligence (XAI) or interfaces that increase transparency, may offer useful information for enhancing system architecture. Moreover, incorporating the viewpoints of both healthcare and insurance professionals may lead to a deeper understanding of the obstacles involved in implementing and embracing AI technologies. Future research can help create inclusive, moral, and easy-to-use AI systems that better meet customer demands and legal requirements in the health insurance sector by broadening the scope and depth of investigation.

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