

# Digital Trust and AI-Driven Insurance Services: Their Impact on Policyholder Perception and Adoption in Tamil Nadu

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## Abstract

The adoption of artificial intelligence (AI) is transforming the insurance industry. Given the growing digitalization of the market in emerging economies such as India, understanding how consumers perceive and are likely to adopt insurance services provided through AI-driven channels is critical for insurance providers and technology vendors. This study focuses on Tamil Nadu, India, and investigates the impact of digital trust and various attributes of AI-driven insurance services on policyholder perception and adoption intention. This study incorporates factors such as algorithmic transparency, digital trust, AI service quality, perceived usefulness, perceived risk, social influence, and policyholder perception into an integrated framework to understand the concept of adoption intention. This study utilized a cross-sectional research design, in which a questionnaire survey of 628 respondents was conducted. The results obtained from applying Structural Equation Modeling (SEM) with the help of the AMOS software revealed that the measurement model obtained was adequate, exhibiting high reliability, convergent validity, and discriminant validity. However, the structural model did not follow the conventional path of technology adoption, as the hypothesized relationships between digital trust, perceived usefulness, perceived risk, social influence, and adoption intention were found to be statistically insignificant. These results suggest the emergence of a 'post-adoption behavioral paradigm', whereby digital trust is perceived as a natural expectation, risks are normalized, and individuals display increased individualization in their technology adoption decisions. Most importantly, the relationship between policyholder perception and adoption intention was found to be weak. The study offers new insights through its emerging market-based perspective and helps further knowledge about AI-based insurance adoption by suggesting a move towards experience-oriented and nonlinear theories. Further research must explore the threshold of trust, the process of risk normalization, the role of digital literacy and past experience, and behavioral change among policyholders to create future-generation AI adoption models for digital finance.

**Keywords:** Artificial Intelligence, Digital Trust, Algorithmic Transparency, AI Service Quality, Perceived Usefulness, Perceived Risk, Policyholder Perception, Adoption Intention, Insurance Technology.

## Introduction

The global insurance industry is rapidly transforming itself in the face of the digital revolution driven by the emergence of artificial intelligence (AI), big data, and platform ecosystems. Historically, the insurance industry has suffered from inefficiencies stemming from manual intervention, high information asymmetry, and rigid service models (Kodete, 2021). AI-based digital technologies are increasingly transforming the insurance industry. Chatbots are being deployed to deliver customer services at reduced costs,

automated underwriting engines are reducing underwriting timelines, big data-powered predictive analytics are revolutionizing risk assessment, and machine learning-based algorithms are delivering fraud detection solutions at a pace and scale never witnessed before (Chellasamy et al., 2025; Hasbullah et al., 2026). These digital solutions are transforming the insurance value chain, reducing operational costs, enabling time-sensitive decisions, and providing superior customer experiences (Ingrid & Karanveer, 2025). In India, the digitalization of insurance services has recorded exponential growth over the last decade, with increased Internet penetration and smartphone adoption (Gohil & Salehbhai, 2025). The digital insurance ecosystem, comprising online insurance marketplaces, digital general insurance, and health insurance products, has taken center stage. The presence of industry leaders like LIC Digital and Policybazaar has grown exponentially, enabling customers to compare, purchase, and even lodge claims online (Kurian & Swarupa, 2025). AI-and machine learning-powered tools provide customers with intelligent recommendations and automate a range of processes for insurance companies (Jain et al., 2025). Moreover, the rapid emergence of InsurTech start-ups and established players is transforming the Indian insurance landscape by deploying innovative technology solutions and disrupting traditional insurance models to embrace a customer-centric approach (Shukor, 2020).

AI, computer vision, and IoT have started making their presence felt in the insurance domain; however, the adoption of these technologies is slow, particularly in emerging markets such as India (Abdikerimova & Feng, 2022). While infrastructure, talent, scale, and cost are critical drivers of technology adoption, in the specific context of insurance, trust is equally, if not more, important. In essence, as insurance moves to a digital native business model, issues of transparency of algorithms in AI-mediated insurance services are gaining salience (Kumar, 2025). Unlike human-to-human interaction, in AI-to-human interaction, accountability and fairness can become difficult to establish in the absence of explainability of the underlying processes and algorithms that drive decisions around claims processing, premium rating, underwriting, etc. (Noto, 2017). Thus, digital trust

emerges as an important antecedent that influences the acceptability of Insurance 4.0 among policyholders in the new economy (Ravi & Vedapradha, 2024). Other factors that would make policyholders worried about their data, and therefore, about AI-mediated insurance services include the risk of data breaches, lack of understanding of bias embedded in the data, and black box algorithms (Alfiero et al., 2022). The literature has started to use terms such as “algorithmic trust” to focus on some of these emerging challenges in the digital age of insurance (Ahmad & Saxena, 2022).

With the rapid adoption of information and communication technology in Tamil Nadu, economic growth and digital technology adoption are increasingly interrelated, even as concerns about unemployment are growing as AI increasingly replaces human labor. To address these issues and succeed in future markets, the development of Artificial Intelligence-driven insurance services in the region is crucial. Opportunities abound, especially given the State’s high literacy rates and increasing digital penetration; however, challenges persist, such as differing levels of digital literacy, socio-economic realities, and varying levels of trust in technology, which are all roadblocks to achieving universal access to these innovative financial products (Cognizant, 2016). Therefore, it is critical to examine the connection between digital trust and the attributes of AI-driven insurance services and how this influences the perception and adoption of policyholders. This study explores the association between digital trust and AI-driven insurance services and their combined effect on policyholders’ perceptions and adoption in Tamil Nadu. It identifies the determinants of the adoption of insurance AI-driven services and offers strategic recommendations for increased adoption. The findings of this study will be relevant for insurance firms, government officials, and innovators tasked with developing Insur Tech solutions for the region.

This study contributes to the current literature on the adoption of artificial intelligence technologies in the financial services sector in various ways. First, while previous studies have mostly considered aspects such as technology acceptance, trust, or service quality individually, this study aimed to create and

empirically test an integrated theoretical framework, including algorithmic transparency, digital trust, AI service quality, perceived usefulness, perceived risk, policyholder perception, social influence, and adoption intention in one structure. Second, this study incorporates algorithmic transparency as an antecedent of digital trust in the insurance domain, addressing a significant gap in the current literature on InsurTech, where there is little research on transparency-based mechanisms. Finally, this is one of the first empirical studies on the adoption of AI in insurance in Tamil Nadu.

- RO1: To investigate the effect of Algorithmic Transparency on Digital Trust for AI insurance services.
- RO2: To explore the effect of Digital Trust on Perceived Usefulness, AI Service Quality, Policyholder Perception, and Adoption Intention.
- RO3: To explore the effects of AI Service Quality and Perceived Usefulness on Policyholder Perception.
- RO4: To test the effects of Perceived Risk, Policyholder Perception, and Social Influence on Adoption Intention.
- RO5: To validate an integrated structural model that explains policyholders' adoption of AI insurance services in Tamil Nadu.

## Literature Review

The insurance industry is experiencing a revolution fueled by innovation and the adoption of AI technologies into the value creation process to automate, anticipate, and personalize underwriting, claims processing, and customer service, detecting and preventing fraud, as well as in many other activities (Bittini et al., 2022; Kumar, 2025). While InsurTech improves operations, reduces costs, and delivers value to policyholders, new challenges regarding trust must be addressed to build acceptance of innovative insurance offerings and improve distribution and customer service models (Abdikerimova & Feng, 2022; Brophy, 2020). Ultimately, the acceptability of risk by insureds, as well as that of underwriters, drives the success of innovative solutions. In relation to the adoption of AI-driven insurance services, empirical evidence has found that perceived usefulness and ease of

use of technology are key drivers of behavioral intentions to adopt, and later extensions to these models incorporate additional factors, including trust and perceived risk (Cao et al., 2020). The planned behavior framework has also been extended to AI adoption intentions, and in this extended version, performance expectancy, effort expectancy, and social influence join attitude, subjective norms, and perceived behavioral control as determinants of behavioral intentions (Farrell et al., 2019). When it comes to digital financial service adoption, such as insurance, planned behavior has been extended and combined with trust-based constructs. For a growing number of consumers, the most important factor when interacting with financial service providers is trust in AI technology to manage their data and make key financial decisions (Gupta et al., 2022). Users' trust in AI systems such as chatbots and robo-advisors is significantly impacted by factors related to system reliability (i.e., accuracy and efficiency), transparency, privacy and security of customers' data, and the credibility of the insurance institution (Lanfranchi & Grassi, 2022; Ravi & Vedapradha, 2024). By building greater trust, insurers can reduce uncertainty, generate greater value for their customers, and drive their intentions to adopt novel and innovative insurance services. Trust in InsurTech is multifaceted, extending to trust in insurers, digital channels, and technology-driven algorithms that enable automated decisions (Zarifis et al., 2023). While service quality has long been recognized as an important predictor of customer satisfaction with traditional insurance services, the impact of service quality on customer satisfaction with AI-driven insurance services has only recently begun to receive attention (Eckert & Osterrieder, 2020). Studies have shown that the digital insurance services developed and offered by insurers have the potential to greatly enhance service quality by enabling insurers to provide services that are more responsive, personal, and efficient (Hasbullah et al., 2026; Accenture, 2017). Furthermore, customer satisfaction with insurance services has been shown to positively affects customer adoption intentions for digital insurance services. In addition to service quality, perceived usefulness has long been recognized as a critical

predictor of adoption. Usefulness is defined as “the degree that an information technology application is perceived as being useful to an individual, group within an organization, or organization” (Alfiero et al., 2022; Ahmadi, 2017). In the context of AI-driven insurance services, usefulness is often perceived as enabling users to process applications faster, make better decisions, and improve performance (Chellasamy et al., 2025; Corea, 2017). Studies have found that usefulness is the strongest predictor of users’ perceptions of AI-driven insurance services and that it has a positive effect on users’ adoption intentions. Intermediate constructs, such as policyholder perception, also play an important role. Positive perceptions of the services offered by insurers, such as convenience, efficiency, and reliability, boost adoption intentions (Khare & Singh, 2010). Such perceptions are influenced by various factors, including technological and psychological factors (Aitken, 2022; Eling et al., 2022). The trust that customers have in insurers and their insurance services is considered one of the most important factors influencing the adoption of AI-driven insurance services (Tian & Liu, 2024). Trust is often seen as a mediating variable between technology adoption models, and social influence has long been recognized as an important predictor of technology adoption (Tomasi & Ilankadhir, 2024). Unlike in individualistic societies such as the US, social norms in collectivistic societies such as China have been shown to play a particularly important role in shaping technology adoption decisions (Alfiero et al., 2022). Word-of-mouth recommendations from peers, family, and social media contacts are considered the most influential form of social media in technology adoption and have been found to positively affect the adoption of digital insurance services (Ingrid et al., 2025). While insurance adoption through AI has been related to several factors, such as trust, perceived usefulness, service quality, and perceived risk, some gaps persist. The lack of incorporation of AI-specific constructs, such as algorithmic transparency, limited concentration on digital trust as a core mediator, paucity of empirical evidence from emerging markets, such as India, and scanty discussion on perception as a mediator are some of the pertinent gaps. This study addresses these gaps by conceptualizing an

integrated model that incorporates digital trust, AI service quality, algorithmic transparency, perceived risk, and policyholder perception as antecedents to insurance adoption through AI.

Prior literature on the adoption of digital financial services found trust, perceived usefulness, and service quality to be important determinants of technology adoption; however, their findings have not been consistent. Although TAM has emphasized perceived usefulness as the prime driving factor behind the decision of technology adoption, further investigations have found that the usefulness construct cannot fully account for adoption decisions made by users in AI-enabled environments, where the transparency of decision-making is quite low (Cao et al., 2020; Alfiero et al., 2022). However, although UTAUT research considers performance expectancy and social influence as two leading drivers of technology adoption, digital financial services have proven inconsistent regarding the effect of social influence on decisions, especially when dealing with technologically experienced users who tend to rely on individual evaluation (Farrell et al., 2019; Tomasi & Ilankadhir, 2024). Overall, trust-related literature suggests a positive correlation between digital trust and intentions to adopt technology; however, most studies are devoted to institutional trust and credibility, ignoring the effects of algorithmic trust, transparency, and explainability (Gupta et al., 2022; Ravi & Vedapradha, 2024). Furthermore, the existing body of research conducted in developed countries makes many assumptions about the level of digital maturity and digital literacy, but the studies conducted in developing countries reveal greater apprehensions on issues such as privacy, security, and fairness of AI systems (Abdikerimova & Feng, 2022; Ahmad & Saxena, 2022). Previous literature also provides inconsistent findings on the issue of risk perceptions. Although there is evidence that risk is a major barrier to adopting AI technologies, recent research shows that consumers tend to accept privacy and algorithmic risks as part of digital service consumption. Moreover, previous studies have investigated the adoption phenomenon using direct and linear approaches while ignoring the possible interaction effects of variables such as perceptions, trust, and service quality. Therefore, there is a major

gap in the literature regarding the joint effects of variables such as algorithmic transparency, digital trust, AI service quality, perceived usefulness, perceived risk, policyholder perception, and social influence on the adoption of AI-powered insurance in emerging economies such as Tamil Nadu.

## Research Methodology

This study attempts to identify the relationship between digital trust and AI-driven insurance services with policyholder perception and adoption intention. This study used a quantitative cross-sectional approach. A primary data source was adopted for this study, and a well-structured questionnaire was developed to collect data from all policyholders and potential users of digital insurance services in Tamil Nadu. A five-point Likert scale was used as a measurement tool to measure the degree to which participants agreed with the items on the scales. The selected items to measure the constructs of Algorithmic Transparency, Digital Trust, AI Service Quality, Perceived Usefulness, Perceived Risk, Social Influence, Policyholder Perception, and Adoption Intention were drawn from existing theories and validated studies. A total of 628 participants were selected using purposive sampling. Measurement items were adopted from existing theories to establish content validity. The items for measuring reliability and construct validity were examined using Cronbach's alpha, composite reliability, and average variance extracted (AVE). Structural equation modeling (SEM) was employed using AMOS to test the measurement and structural models through path analysis, mediation effect, and model fit.

## Result and Discussion

The Socio-Demographic Profile and Digital Insurance Engagement (Table 1) shows that the age distribution is moderately right-skewed and presents the highest concentration in the 25–35 years (33.1%) and 36–45 years (25.0%) age groups, with a combined share of nearly 58%. However, all age groups were included in the study, thereby allowing the examination of age as a moderating variable. On the other hand, the study's sample presented a moderately balanced gender distribution, with 53.3% males and 46.7% females. This near-parity further strengthens the sampling validity in terms of the study's objectives. The distribution of occupational categories presented quasi-normality, with the majority being private employees (31.7%), followed by students (22.9%) and self-employed individuals (20.5%). Private employees are followed by those with other sources of income. This distribution supports external validity due to the varying levels of income and engagement in financial activities. The educational distribution is nearly normally distributed (Table 3), with the majority of respondents having undergraduate (32.5%) and postgraduate (30.9%) degrees. This was followed by a higher than expected percentage of school dropouts (18.0%), which could be attributed to the digital naivety of this segment and needs to be addressed for broader digital inclusion. This distribution supports the findings related to the perceived ease of use of AI in insurance and speaks highly of the cognitive readiness of the sample for the adoption of AI-driven insurance services. The distribution of income shows a slight right skew, with the majority of respondents having an income between 20,001 and 40,000 (28.8%) and 40,001 and 60,000 (26.6%). This supports the findings related to the perceived affordability of digital insurance offerings. Therefore, middle-income groups will remain the core target market for digital insurance services. However, there is a reasonable presence of lower (21.3%) and higher (11.5%) income groups in the study. This will help in studying the intent to adopt technology-based solutions and services for insurance needs, along with perceived risk and perceived value.

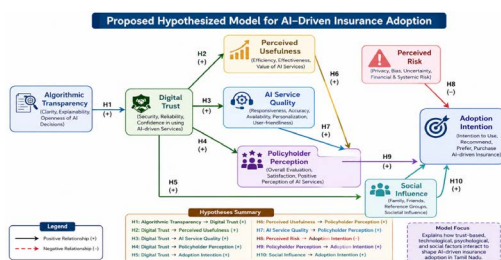


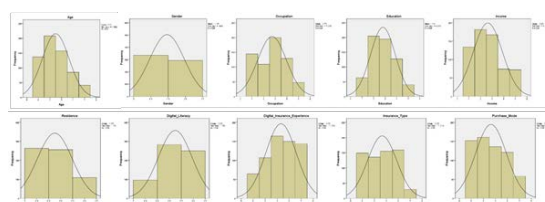
Figure 1 Hypothesized Model

**Table 1 Comprehensive Socio-Demographic Profile and Digital Insurance Engagement Characteristics of Respondents in Tamil Nadu**

| Age                      | Frequency | Percent | Income                       | Frequency | Percent |
|--------------------------|-----------|---------|------------------------------|-----------|---------|
| Below 25 years           | 137       | 21.8    | Below 20,000                 | 134       | 21.3    |
| 25–35 years              | 208       | 33.1    | 20,001 – 40,000              | 181       | 28.8    |
| 36–45 years              | 157       | 25.0    | 40,001 – 60,000              | 167       | 26.6    |
| 46–55 years              | 85        | 13.5    | 60,001 – 80,000              | 74        | 11.8    |
| Above 55 years           | 41        | 6.5     | Above 80,000                 | 72        | 11.5    |
| Gender                   | Frequency | Percent | Digital Literacy             | Frequency | Percent |
| Male                     | 335       | 53.3    | Low                          | 96        | 15.3    |
| Female                   | 293       | 46.7    | Moderate                     | 282       | 44.9    |
| Education                | Frequency | Percent | High                         | 250       | 39.8    |
| School Level             | 63        | 10.0    | Digital Insurance Experience | Frequency | Percent |
| Undergraduate            | 204       | 32.5    | Never                        | 64        | 10.2    |
| Postgraduate             | 194       | 30.9    | Rarely                       | 107       | 17.0    |
| Professional Degree      | 127       | 20.2    | Occasionally                 | 164       | 26.1    |
| Doctorate                | 40        | 6.4     | Frequently                   | 150       | 23.9    |
| Occupation               | Frequency | Percent | Regular                      | 143       | 22.8    |
| Student                  | 144       | 22.9    | Not yet purchased            | 58        | 9.2     |
| Government Employee      | 109       | 17.4    | Residence                    | Frequency | Percent |
| Private Sector Employee  | 199       | 31.7    | Urban                        | 263       | 41.9    |
| Self-employed / Business | 129       | 20.5    | Semi-Urban                   | 256       | 40.8    |
| Unemployed / Others      | 47        | 7.5     | Rural                        | 109       | 17.4    |

The distribution of digital literacy is highly skewed towards moderate and high levels of literacy, with 44.9% of respondents having moderate literacy, 39.8% having high literacy, and only 15.3% having low literacy. This means that nearly 85% of the sample was capable of using AI-driven platforms. From a theoretical perspective, this reinforces digital literacy as a facilitating condition and critical moderating variable that strengthens the impact of digital trust on adoption intention. The distribution of digital insurance experience is near normal, with a greater than usual concentration at the occasional, frequent, and regular ends of the spectrum. This means that instead of just having experienced it, consumers are also active participants in the digitalization of the insurance experience. The 10.2% of non-users are further diluted by the 26.1% of consumers who occasionally experience digital insurance, 23.9% who frequently experience it, and

22.8% who regularly experience it. The residential distribution was fairly balanced between urban and semi-urban areas, with 41.9% and 40.8%, respectively. However, 17.4% of rural consumers suggest that the digitalization experience is currently growing beyond metropolitan areas to semi-urban regions. This contrasts with the traditional urban-centric perspective of digital adoption and indicates that AI-enabled financial services can reach a wider audience across the country.



**Figure 2 Distributional Analysis of Socio-Demographic Attributes and Digital Insurance Behavior of Respondents**

Strong intra-construct correlations among the measures suggest a strong measurement structure with high internal consistency and convergent validity across all latent variables. Additionally, predominantly low to moderate inter-construct correlations indicate discriminant validity among the study's constructs. High correlations among the measures of policyholder perception potentially suggest redundancy that requires confirmatory testing. In contrast to prior linear approaches to studying technology adoption, findings demonstrate that trust and cognitive evaluations serve the role of transmission or mediators in driving adoption intention for AI-powered insurance technologies. Further structural inspection is necessary to fully uncover the determinants of adoption.

The results from the rotated component matrix (Table 2) indicate a very robust and

well-structured factor solution for the items, with each item loading very strongly and distinctively on its respective construct. All constructs, Algorithmic Transparency, Digital Trust, AI Service Quality, Perceived Usefulness, Perceived Risk, Policyholder Perception, Social Influence, and Adoption Intention, have high factor loadings (all above 0.87) and are free from any significant cross-loadings. The results also indicate excellent factorial purity and clear construct distinctiveness between the factors. The value of KMO for factor analysis is adequate at 0.819, while the total variance explained by the eight factors is 61.137%. Composite Reliability (CR) and Average Variance Extracted (AVE) values support high internal consistency and convergent validity for all constructs, with  $\sqrt{\text{AVE}}$  supporting discriminant validity.

**Table 2 Rotated Component Matrix, Reliability, and Convergent Validity Assessment of Measurement Constructs Using Principal Component Analysis**

| Rotated Component Matrix <sup>a</sup> |           |   |      |      |      |   |      |   |
|---------------------------------------|-----------|---|------|------|------|---|------|---|
|                                       | Component |   |      |      |      |   |      |   |
|                                       | 1         | 2 | 3    | 4    | 5    | 6 | 7    | 8 |
| AT1                                   |           |   | .934 |      |      |   |      |   |
| AT2                                   |           |   | .923 |      |      |   |      |   |
| AT3                                   |           |   | .940 |      |      |   |      |   |
| AT4                                   |           |   | .940 |      |      |   |      |   |
| DT1                                   |           |   |      | .922 |      |   |      |   |
| DT2                                   |           |   |      | .913 |      |   |      |   |
| DT3                                   |           |   |      | .929 |      |   |      |   |
| DT4                                   |           |   |      | .925 |      |   |      |   |
| ASQ1                                  | .875      |   |      |      |      |   |      |   |
| ASQ2                                  | .911      |   |      |      |      |   |      |   |
| ASQ3                                  | .929      |   |      |      |      |   |      |   |
| ASQ4                                  | .931      |   |      |      |      |   |      |   |
| ASQ5                                  | .932      |   |      |      |      |   |      |   |
| PU1                                   |           |   |      |      | .887 |   |      |   |
| PU2                                   |           |   |      |      | .922 |   |      |   |
| PU3                                   |           |   |      |      | .904 |   |      |   |
| PU4                                   |           |   |      |      | .923 |   |      |   |
| PR1                                   |           |   |      |      |      |   | .879 |   |
| PR2                                   |           |   |      |      |      |   | .895 |   |
| PR3                                   |           |   |      |      |      |   | .895 |   |
| PR4                                   |           |   |      |      |      |   | .897 |   |

|                                                        |       |       |       |       |       |       |       |       |
|--------------------------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| PP1                                                    |       | .988  |       |       |       |       |       |       |
| PP2                                                    |       | .945  |       |       |       |       |       |       |
| PP3                                                    |       | .960  |       |       |       |       |       |       |
| PP4                                                    |       | .986  |       |       |       |       |       |       |
| SI1                                                    |       |       |       |       |       |       |       | .918  |
| SI2                                                    |       |       |       |       |       |       |       | .912  |
| SI3                                                    |       |       |       |       |       |       |       | .913  |
| AI1                                                    |       |       |       |       |       | .899  |       |       |
| AI2                                                    |       |       |       |       |       | .931  |       |       |
| AI3                                                    |       |       |       |       |       | .956  |       |       |
| AI4                                                    |       |       |       |       |       | .860  |       |       |
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.819 |       |       |       |       |       |       |       |       |
| Total Variance Explained                               | 4.506 | 3.910 | 3.793 | 3.447 | 3.285 | 3.041 | 2.956 | 2.427 |
| CR                                                     | 0.95  | 0.98  | 0.94  | 0.94  | 0.92  | 0.93  | 0.91  | 0.90  |
| AVE                                                    | 0.79  | 0.92  | 0.80  | 0.79  | 0.74  | 0.78  | 0.71  | 0.75  |
| √AVE                                                   | 0.89  | 0.96  | 0.89  | 0.89  | 0.86  | 0.88  | 0.84  | 0.87  |
| Extraction Method: Principal Component Analysis.       |       |       |       |       |       |       |       |       |
| Rotation Method: Varimax with Kaiser Normalization.    |       |       |       |       |       |       |       |       |
| a. Rotation converged in 5 iterations.                 |       |       |       |       |       |       |       |       |

The Maximum Likelihood Estimation results of the measurement model (Table 3) provide strong evidence of validity for the multidimensional framework for measuring digital trust and AI-driven insurance adoption in Tamil Nadu. All the observed indicators had very high loadings on their respective latent constructs ( $p < 0.001$ ). The standardized factor loadings for all the constructs were very high at 0.813, 0.918, 0.999, 0.876, and 0.896 for DX, SX, AT, DT, and ASQ, respectively. The critical ratios of all the observed indicators were extremely high, indicating very high convergent validity and internal consistency for all the constructs. The AT

construct had very high loadings for understanding, decision-making explanations, decision-making processes, and data usage by AI systems. The findings indicate that policyholders are not passive recipients of information and scrutinize the levels of interpretability that AI systems offer. While policyholders may cognitively perceive transparency in AI systems, they may not automatically translate this ‘knowledge’ into trust. In the contemporary context, they may rely on other determinants, such as assurance from institutional sources or positive past experiences, before trusting AI systems.

**Table 3: Standardized Factor Loadings and Measurement Model Assessment of Latent Constructs, (Maximum Likelihood Estimates; Regression Weights)**

| Measured Variables |      | Latent Variables | Estimate | S.E. | C.R.   | P   |
|--------------------|------|------------------|----------|------|--------|-----|
| AT4                | <--- | AT               | .923     |      |        |     |
| AT3                | <--- | AT               | .924     | .025 | 40.454 | *** |
| AT2                | <--- | AT               | .892     | .027 | 36.512 | *** |
| AT1                | <--- | AT               | .913     | .026 | 39.035 | *** |
| DT4                | <--- | DT               | .904     |      |        |     |
| DT3                | <--- | DT               | .906     | .028 | 35.371 | *** |
| DT2                | <--- | DT               | .882     | .029 | 33.233 | *** |

|      |      |     |      |      |         |     |
|------|------|-----|------|------|---------|-----|
| DT1  | <--- | DT  | .897 | .029 | 34.525  | *** |
| ASQ5 | <--- | ASQ | .921 |      |         |     |
| ASQ4 | <--- | ASQ | .925 | .026 | 40.675  | *** |
| ASQ3 | <--- | ASQ | .921 | .025 | 40.100  | *** |
| ASQ2 | <--- | ASQ | .883 | .027 | 35.622  | *** |
| PU4  | <--- | PU  | .904 |      |         |     |
| PU3  | <--- | PU  | .874 | .032 | 32.055  | *** |
| PU2  | <--- | PU  | .903 | .031 | 34.378  | *** |
| PU1  | <--- | PU  | .840 | .032 | 29.446  | *** |
| PR4  | <--- | PR  | .883 |      |         |     |
| PR3  | <--- | PR  | .885 | .033 | 30.145  | *** |
| PR2  | <--- | PR  | .839 | .034 | 27.492  | *** |
| PR1  | <--- | PR  | .813 | .036 | 26.017  | *** |
| PP4  | <--- | PP  | .995 |      |         |     |
| PP3  | <--- | PP  | .940 | .014 | 66.077  | *** |
| PP2  | <--- | PP  | .906 | .017 | 52.333  | *** |
| PP1  | <--- | PP  | .999 | .005 | 206.828 | *** |
| AI4  | <--- | AI  | .825 |      |         |     |
| AI3  | <--- | AI  | .961 | .034 | 31.894  | *** |
| AI2  | <--- | AI  | .901 | .035 | 28.939  | *** |
| AI1  | <--- | AI  | .855 | .035 | 26.578  | *** |
| SI3  | <--- | SI  | .867 |      |         |     |
| SI2  | <--- | SI  | .866 | .037 | 27.041  | *** |
| SI1  | <--- | SI  | .881 | .033 | 27.532  | *** |
| ASQ1 | <--- | ASQ | .826 | .031 | 30.283  | *** |

Digital Trust had very high loadings on security, reliability, and confidence in using insurance services. AI Service Quality had very high loadings on responsiveness, accuracy, availability, user-friendliness, and personalization of services. ASQ had a significant influence on DX and SX, but the findings for subsequent variables were disappointing. Perceived Usefulness (PU) is a key determinant of technology adoption behavior. Based on extensive validation results that establish high levels of indicator reliability for PU (0.840–0.904), this study questions the construct's significance in predicting Policyholder Perception (PP) of AI-driven insurance. While the functional benefits of efficiency and cost savings remain relevant, they no longer suffice to predict perceptions of services that are inherently experiential. The construct of Perceived AI Risk (PR), encompassing concerns about privacy, bias, financial uncertainty, and system errors, obtained

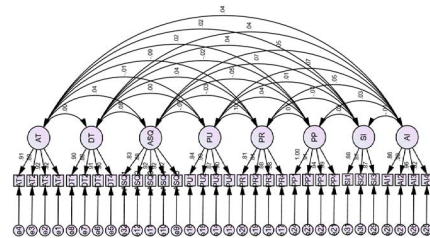
high levels of indicator reliability (0.813–0.885). The findings also reveal extremely high loadings (0.906–0.999) for the construct of Policyholder Perception (PP) that form a unified evaluation of AI-driven insurance services and tally with a cognitive scheme that incorporates users' experiences of benefits, convenience, and service quality. Notably, however, PP explains the least variation in Adoption Intention (AI), pointing to a crucial break in the linkage between positive perceptions of the expected consequences of adoption and intentions to adopt AI-driven insurance services.

The measurement model (Figure 2) demonstrates strong construct validity for Social Influence (SI) (0.865–0.881), and its effect on adoption intention is found to be insignificant. This finding suggests the increasing individualization of AI-based insurance decision-making processes, moving away from collective influence. The factor model for Adoption

Intention (AI) (0.825–0.961) captures intention, recommendation, preference, and purchase plans adequately. While the measurement model was strong in terms of construct validity, the structural model presented a mixed scenario with multiple non-significant paths. Thus, this study provides a critical theoretical contribution by highlighting that insurance adoption in Tamil Nadu is not predicted by the traditional linear set of antecedents. Instead, it is an integrated set of cognition, affect, and behavior that determines AI-driven insurance adoption.

The structural model fit indices (Table 4) revealed a very good fit of the proposed framework in predicting digital trust and adoption of AI-driven general insurance in Tamil Nadu. The overall model fit was adequate. The normed chi-square ( $\chi^2/df$ ) was

2.727, below the threshold of 3.00 for a good balance between model fit and complexity. The Root Mean Square Residual (RMR) of .017 was less than half of the cutoff value of .08, signifying a very good fit.



**Figure 3 Measurement Model of Latent Constructs and Observed Indicators Using Confirmatory Factor Analysis (CFA)**

**Table 4 Model Fit Indices and Goodness-of-Fit Evaluation of the Measurement Model**

| Index                 | Obtained Value | Recommended Value | Interpretation |
|-----------------------|----------------|-------------------|----------------|
| $\chi^2/df$ (CMIN/DF) | 2.727          | < 3.00            | Good Fit       |
| RMR                   | 0.017          | < 0.08            | Excellent Fit  |
| GFI                   | 0.889          | $\geq 0.90$       | Marginal Fit   |
| AGFI                  | 0.866          | $\geq 0.80$       | Acceptable Fit |
| NFI                   | 0.945          | $\geq 0.90$       | Good Fit       |
| RFI                   | 0.938          | $\geq 0.90$       | Good Fit       |
| IFI                   | 0.965          | $\geq 0.90$       | Excellent Fit  |
| TLI                   | 0.960          | $\geq 0.90$       | Excellent Fit  |
| CFI                   | 0.965          | $\geq 0.90$       | Excellent Fit  |
| PNFI                  | 0.831          | $\geq 0.50$       | Good Fit       |
| PCFI                  | 0.848          | $\geq 0.50$       | Good Fit       |
| RMSEA                 | 0.052          | < 0.08            | Good Fit       |
| PCLOSE                | 0.124          | > 0.05            | Close Fit      |
| HOELTER (.05)         | 257            | > 200             | Adequate       |

Although the Goodness-of-Fit Index (GFI) of .889 was less than the threshold value of .90, it was acceptable considering the complexity of the model. The Adjusted Goodness-of-Fit Index (AGFI) of .866 was greater than the minimum acceptable level of .80, hence signifying an adequate fit of the model after adjusting for degrees of freedom. The consistency in good fit in multiple categories (absolute, incremental, and parsimony) thus provides strong evidence that the proposed integrated model captured the underlying behavioral dynamics of AI-driven insurance adoption effectively and precisely, except for the slightly marginal GFI score. This

score may be attributed to the complexities inherent in measuring multidimensional constructs such as digital trust, perceived risk, and AI service quality.

### Managerial Implication

Several crucial implications for insurance companies, InsurTech providers, policymakers, and regulators interested in the faster adoption of AI-based insurance in developing digital markets such as Tamil Nadu can be derived from the results of this study. One of the most significant insights provided by this study is that digital trust operates as a foundational expectation, not a determinant of

adoption intention, meaning that simply creating an environment of trust does not ensure that consumers will decide to use AI insurance. Therefore, insurance companies must move from traditional approaches to building trust to developing a transparent, explainable, and experiential digital environment. First, insurance companies must focus on algorithmic transparency along the entire value chain of the insurance business. Automated processes of risk assessment and insurance evaluation through AI tools should include the use of Explainable Artificial Intelligence, thus allowing customers to understand how automated decisions are made. To increase customers' confidence in algorithms, companies should present simplified explanations of decisions, their confidence levels, and AI explanation dashboards. Second, insurance companies need to improve their information governance and cyber security framework by implementing internationally accepted information security standards and transparently communicating these strategies with policyholders. Communicating privacy protection, encryption, consent procedures, and adherence to new AI governance regulation standards will boost their credibility. The presentation of cybersecurity certification and regulatory compliance badges will increase customers' confidence in AI-driven insurance products. Third, managers should understand that the quality of AI services is an important determinant of customers' general perception of the digital insurance experience, even if it does not have a direct effect on the adoption of such innovations. Therefore, insurance companies must implement intelligent customer support solutions that enable real-time claim tracking, customized policy recommendations, risk alerts, omnichannel service delivery, and seamless interfaces between mobile apps, websites, and customer service agents. Fourth, insurance firms should develop robust programs to educate people on how to be conversant with the use of digital tools through AI literacy training to enhance the digital confidence of different consumer categories. Interactive training programs, educational campaigns, digital awareness workshops, and clear explanations of AI use can demystify the process of automated decision-making and make customers conversant with the use of AI

in insurance products. Specific focus should be on low-literate digital consumers to ensure that there is no technology exclusion in terms of digital financial inclusion. Fifth, insurance companies and regulators should work together to build ethical AI governance frameworks that emphasize transparency, fairness, accountability, data protection, and discrimination-free algorithms in AI processes. Independent audits of AI algorithms, publication of fairness reports, bias evaluations, and certification of AI systems by regulators can increase public confidence in AI. The final implication is that the minimal impact of social influence on adoption intention indicates that modern policyholders are more dependent on independent evaluations than recommendations provided by their families or peers. In this connection, marketing policies must go beyond traditional word-of-mouth campaigns and instead emphasize personalization, digital customer experience, and factual presentations of the advantages of artificial intelligence. It is also necessary to continue providing hybrid services based on human-AI interaction, especially when dealing with critical situations such as claims controversies, fraud investigations, and difficult underwriting cases. Human-AI strategies are expected to increase customer satisfaction and contribute to sustainable digital transformation in the insurance industry.

### Limitations

Although this study is valuable from both theoretical and practical perspectives, it faces certain limitations that must be considered when interpreting the findings. First, the study uses a cross-sectional approach and thus obtains the perception of policyholders at one point in time. As AI solutions and their attitudes are rapidly changing, longitudinal approaches should provide more information on the dynamics of trust formation and perception evolution. Second, the research was conducted only with policyholders in Tamil Nadu; therefore, the results cannot be generalized to other Indian states or countries worldwide with different infrastructures, regulatory frameworks, and cultures. It would be useful to conduct comparative research across regions and countries. Third, the data for the study were obtained through self-reporting; thus, the study is exposed to common method variance,

social desirability bias, and subjective responses of the respondents. Fourth, while the developed framework included aspects such as algorithmic transparency, digital trust, AI service quality, perceived usefulness, perceived risk, policyholders' perception, social influence, and adoption intention, there were many more contextual factors, such as digital literacy, AI literacy, institutional reputation, regulatory confidence, financial literacy, personality characteristics, and digital service usage experience, which could have been considered but were not. Finally, although the measurement model was highly reliable and valid, several relationships in the structural model did not emerge as statistically significant, although there was an overall good fit of the model. This indicates that AI-enabled insurance adoption may have some nonlinear or interactive influences that cannot be explained by covariance-based SEMs.

### Future Research Direction

The findings and limitations of this study provide several avenues for further research. First, future research in this field should go beyond existing traditional models of technology acceptance and design more complex and sophisticated theories that can capture the complexity of the interaction between the variables of trust, service quality, user experience, perceived value, and behavioral intention in nonlinear and ecosystem terms. Perspectives from Service-Dominant Logic, Customer Experience Theory, Human-AI Interaction Theory, and Explainable AI might be helpful here. Second, future researchers need to analyze the problem of post-cognitive technology adoption, where digital trust becomes an expectation but not a critical factor in the adoption process. Threshold effects, trust saturation, and the diminishing marginal impact of trust on adoption as digital ecosystems become more advanced can be researched using advanced techniques such as latent class analysis, fuzzy-set qualitative comparative analysis (fsQCA), and nonlinear SEM. Third, future research is needed on the emerging concept of risk normalization in AI-enabled financial services. It is necessary to study how consumers accept various risks related to privacy, bias, security, and automation of decisions

as an ordinary feature of digital services use. The influence of such factors as digital literacy, familiarity with AI, technology anxiety, and institutional trust. Fourth, the lack of social influence found in this study implies a critical shift towards more individualized decision-making in digital financial services. Further research should consider alternative psychological predictors, such as self-efficacy, personal innovativeness, technology readiness, confidence in AI, and digital autonomy, to better predict individuals' behaviors compared to collectivist approaches. Further research should be conducted on new technologies, including generative AI, conversational AI, blockchain-based insurance, IoT telematics, and digital ID technology, to understand how the intelligent next generation of technologies affects trust formation, customer experience, AI ethics, and insurance adoption. This would enable the creation of next-generation theories regarding the adoption of AI-powered financial services in intelligent economies.

### Conclusion

This study investigates the role of digital trust in shaping policyholders' perceptions and adoption of AI-driven insurance services in Tamil Nadu. An integrated framework was developed, comprising algorithmic transparency, AI service quality, perceived usefulness, perceived risk, and social influence. The findings reveal a compelling shift in the 'post-adoption' behavioral paradigm of users. The measurement model had adequate reliability and validity, but the structural relationships deviated significantly from the existing theoretical lens. Users are no longer governed by rational or feature-based expectations. The experience of digital services has 'matured' users to the extent that they anticipate a holistic digital experience before adopting AI-driven insurance services. Digital trust is an expectation, rather than a determinant. Perceived risk does not deter the adoption of AI-driven insurance service. There is a growing normalcy of uncertainty in digital environments. A significant gap exists between positive perception and adoption intentions, challenging the conventional assumption of a direct relationship between perception and adoption. Social factors minimally influence shaping the adoption

intentions of insurance services. The findings of this study thus point towards a ‘post-adoption’ behavioral paradigm. As AI technologies are no longer perceived as innovations in their own right, people make use of them as an integral part of their digital experience, as they do with email, messaging apps, social media, and so on. This study demonstrates that the adoption of AI-driven insurance services in Tamil Nadu is an integrated digital experience. As AI technologies continue to permeate insurance services, future research must move from a simplistic cognitive lens to an integrated framework that captures the nuances of user experience in a mature digital ecosystem. The most important finding of this study is the discovery of a post-adoption behavior framework for AI-based insurance services. While existing technology adoption models emphasize trust, usefulness, risk, and social influence as the main behavioral antecedents, the current study reveals that these parameters operate in a digitally developed environment as preconditions. The current findings contribute to existing adoption theory by suggesting future adoption studies based on experiences rather than cognitive assessments of technological features.

#### Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

#### Conflict of Interest Statement

The authors declare that there is no conflict of interest related to this study.

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