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Artificial Intelligence-Driven Customer Experience and Digital Trust: An Integrated Model of Health Insurance Purchase Behaviour

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Abstract:

The rapid diffusion of artificial intelligence (AI) into the insurance value chain has fundamentally reshaped how consumers search for, evaluate, and purchase health insurance products. Drawing upon the Technology Acceptance Model (Davis, 1989), the extended Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012), and trust-based models of online exchange (Gefen et al., 2003; McKnight et al., 2002), this study develops and empirically tests an integrated model linking AI-driven personalization, AI service quality, and perceived usefulness to health insurance purchase intention through the sequential mediating mechanisms of customer experience and digital trust. Survey responses from 412 health insurance consumers were analysed using a two-step approach (Anderson & Gerbing, 1988) comprising exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and partial least squares structural equation modelling (PLS-SEM) with 5,000 bootstrap subsamples. The measurement model demonstrated strong reliability and validity (Cronbach's $\alpha = 0.822$–0.871; CR = 0.876–0.905; AVE = 0.640–0.704), and discriminant validity was established through both the Fornell–Larcker criterion and the HTMT ratio. All nine hypothesised paths were supported. Customer experience ($\beta = 0.328$, $p < .001$) and digital trust ($\beta = 0.362$, $p < .001$) emerged as the strongest proximal drivers of purchase intention, with the model explaining 42.5% of the variance in purchase intention. The findings underscore that AI capabilities translate into purchase behaviour primarily when they enhance the experiential and trust-related dimensions of the digital insurance journey, offering actionable guidance for insurers, insurtech platforms, and policymakers.

Keywords: *artificial intelligence, customer experience, digital trust, health insurance, purchase intention, PLS-SEM, UTAUT2*

1. Introduction

1.1 Background of the Study

Artificial intelligence has moved from a back-office efficiency tool to a front-line orchestrator of customer interactions across the financial services industry. In the Indian context, the integration of artificial intelligence and financial technology has accelerated across banking and financial services, extending even to the management and development of human resources (V. Jain, 2022a, 2022b). In health insurance specifically, AI now powers personalized premium quotations, conversational chatbots for policy servicing, intelligent underwriting, automated claims triage, and recommendation engines that match consumers with suitable coverage plans. Scholars argue that AI will progressively take over the mechanical and analytical tasks of service delivery while reshaping how firms create experiential value for customers (Huang & Rust, 2018), and that AI represents one of the most consequential forces transforming marketing strategy and customer engagement (Davenport et al., 2020). Kaplan and Haenlein (2019) similarly note that the interpretive and relational implications of AI extend far beyond automation, influencing how consumers perceive, trust, and adopt digitally mediated services.

Health insurance is a particularly meaningful context in which to study these dynamics. India's health insurance market has expanded rapidly amid shifting stakeholder dynamics in the wider healthcare sector, yet continues to confront awareness and penetration challenges (V. Jain, 2022c; V. Jain et al., 2024c). The product is intangible, complex, high-involvement, and contingent on sensitive personal and medical information. Consumers must therefore rely heavily on the quality of the digital experience and on their trust in the platform when deciding whether to purchase. While AI-driven interfaces can reduce search costs and personalize offerings, they can also trigger concerns about data privacy, algorithmic opacity, and fairness. Understanding how AI-driven customer experience and digital trust jointly shape purchase behaviour is thus both theoretically important and managerially urgent.

1.2 Problem Statement and Research Gap

Although a substantial body of research has examined technology acceptance in banking and e-commerce, three gaps remain. First, prior studies tend to examine AI capabilities (e.g., personalization or chatbot quality) or trust in isolation, rather than as an integrated system in which experiential and trust mechanisms transmit the effects of AI features to behaviour. Second, the health insurance purchase context remains under-researched relative to retail e-commerce, despite its distinct risk, privacy, and complexity characteristics. Regional evidence from central India likewise documents persistent gaps in consumer awareness and perception of health insurance, underscoring the need for model-based behavioural research (V. Jain, 2023; V. Jain et al., 2023, 2024a, 2024b). Third, few studies employ a rigorous two-step analytical strategy that combines EFA, CFA, and PLS-SEM to validate both the measurement and structural properties of an integrated AI–experience–trust–behaviour model. This study addresses these gaps by proposing and testing an integrated model in which AI-driven personalization, AI service quality, and perceived usefulness influence health insurance purchase intention through customer experience and digital trust.

1.3 Research Objectives

The study pursues four objectives: (1) to examine the influence of AI-driven personalization, AI service quality, and perceived usefulness on customer experience in digital health insurance platforms; (2) to assess the effects of AI capabilities and customer experience on digital trust; (3) to evaluate the joint influence of customer experience, digital trust, and perceived usefulness on health insurance purchase intention; and (4) to validate an integrated measurement and structural model using EFA, CFA, and PLS-SEM.

1.4 Significance of the Study

Theoretically, the study extends the TAM and UTAUT2 traditions (Davis, 1989; Venkatesh et al., 2012) by embedding AI-specific antecedents and by positioning customer experience and digital trust as the twin experiential–relational conduits through which technology characteristics affect purchase behaviour in a high-risk service category. Practically, the findings help insurers and insurtech platforms prioritise AI investments that demonstrably improve experience and trust, thereby increasing conversion in digital distribution channels. For policymakers, the results highlight the trust-building safeguards required for responsible AI deployment in health financing. Such trust-building matters for the wider digital financial ecosystem—in which institutions such as payment banks increasingly shape financial access across urban and rural India (P. Jain et al., 2025)—and complements broader evidence that technology-enabled management practices are transforming Indian organisations (V. Jain, 2022d, 2022e).

2. Literature Review and Hypothesis Development

2.1 Theoretical Foundation

The study is anchored in three complementary theoretical streams. The Technology Acceptance Model posits that perceived usefulness is a primary determinant of intention to use technology-mediated systems (Davis, 1989). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2) broadens this logic to consumer contexts, incorporating hedonic and habit-related mechanisms that shape adoption (Venkatesh et al., 2012). Finally, trust-based models of online exchange establish that trusting beliefs—competence, benevolence, and integrity—are decisive in environments characterised by uncertainty and information asymmetry (Gefen et al., 2003; McKnight et al., 2002). Because health insurance purchase involves both technology acceptance and risk-laden exchange, an integrated model combining acceptance, experience, and trust mechanisms is theoretically appropriate. Attitudinal–behavioural linkages are further supported by the theory of planned behaviour (Ajzen, 1991) and expectation–confirmation logic in satisfaction formation (Oliver, 1980).

2.2 AI-Driven Personalization (AIP)

AI-driven personalization refers to the system's capacity to tailor product recommendations, premium quotations, content, and interactions to the individual consumer's profile, health needs, and behaviour. Personalization is a hallmark of AI-enabled marketing because machine learning can convert granular customer data into individually relevant offers at scale (Davenport et al., 2020). In insurance, personalization reduces the cognitive burden of comparing complex policy features and signals that the platform understands the customer's specific coverage needs, thereby enriching the experience and fostering confidence in the platform's competence.

2.3 AI Service Quality (ASQ)

AI service quality captures the responsiveness, reliability, accuracy, and assurance delivered by AI-enabled service touchpoints such as chatbots, virtual assistants, and automated claim-status systems. The construct adapts the classical service quality logic of SERVQUAL (Parasuraman et al., 1988) to algorithmic service encounters. Huang and Rust (2018) argue that as AI progresses from mechanical to thinking intelligence, its service quality increasingly determines customers' evaluations of the entire service journey. High-quality AI interactions minimise effort, resolve queries promptly, and reduce the perceived risk of transacting digitally.

2.4 Perceived Usefulness (PU)

Perceived usefulness denotes the degree to which consumers believe that using the AI-enabled insurance platform enhances the effectiveness of their insurance decisions—better plan comparison, faster purchase, and superior post-purchase servicing (Davis, 1989). Within UTAUT2, the closely related performance expectancy construct is consistently the strongest predictor of behavioural intention in consumer technology settings (Venkatesh et al., 2012).

2.5 Customer Experience (CX)

Customer experience is conceptualised as the consumer's holistic cognitive, affective, and sensory evaluation of interactions with the digital insurance platform across the purchase journey. Experience quality integrates ease, enjoyment, coherence, and perceived control, and functions as the experiential residue of technology characteristics. Satisfaction research has long established that favourable experiential evaluations drive downstream attitudes and intentions (Oliver, 1980), and contemporary AI scholarship positions experience as the central battleground of AI-enabled competition (Davenport et al., 2020).

2.6 Digital Trust (DT)

Digital trust reflects the consumer's willingness to be vulnerable to the digital insurance platform based on beliefs about its competence, integrity, benevolence, and data stewardship (McKnight et al., 2002). Trust is particularly consequential in health insurance because consumers disclose sensitive medical information and depend on the insurer's future claim-settlement behaviour. Gefen et al. (2003) demonstrate that trust operates alongside technology acceptance beliefs to shape online purchase intentions, a duality this study preserves.

2.7 Purchase Intention (PI)

Purchase intention represents the consumer's conative readiness to buy or renew a health insurance policy through the AI-enabled digital platform. Intention is the most proximal antecedent of behaviour in planned-behaviour reasoning (Ajzen, 1991) and is the standard endogenous criterion in acceptance research (Davis, 1989; Venkatesh et al., 2012).

2.8 Hypothesis Development

2.8.1 AI Capabilities and Customer Experience

Personalized recommendations reduce search effort and increase relevance, directly enhancing the experiential quality of the journey (Davenport et al., 2020). Similarly, responsive and accurate AI service interactions minimise friction and frustration (Huang & Rust, 2018; Parasuraman et al., 1988), while platforms perceived as useful create a sense of accomplishment and decision confidence (Davis, 1989). Hence:

H1: AI-driven personalization positively influences customer experience.

H2: AI service quality positively influences customer experience.

H3: Perceived usefulness positively influences customer experience.

2.8.2 Antecedents of Digital Trust

Personalization signals competence and customer orientation, while consistent, high-quality AI service performance provides repeated behavioural evidence of reliability—both core bases of trusting beliefs (McKnight et al., 2002). A superior cumulative experience further deepens trust by confirming positive expectations across touchpoints (Gefen et al., 2003; Oliver, 1980). Hence:

H4: AI-driven personalization positively influences digital trust.

H5: AI service quality positively influences digital trust.

H6: Customer experience positively influences digital trust.

2.8.3 Drivers of Purchase Intention

Favourable experiences generate approach motivation and reduce perceived risk, translating into stronger purchase intention (Oliver, 1980). Digital trust lowers the perceived vulnerability of committing to a long-horizon, information-sensitive contract (Gefen et al., 2003; McKnight et al., 2002), while perceived usefulness retains a direct effect on intention consistent with TAM and UTAUT2 (Davis, 1989; Venkatesh et al., 2012). Hence:

H7: Customer experience positively influences health insurance purchase intention.

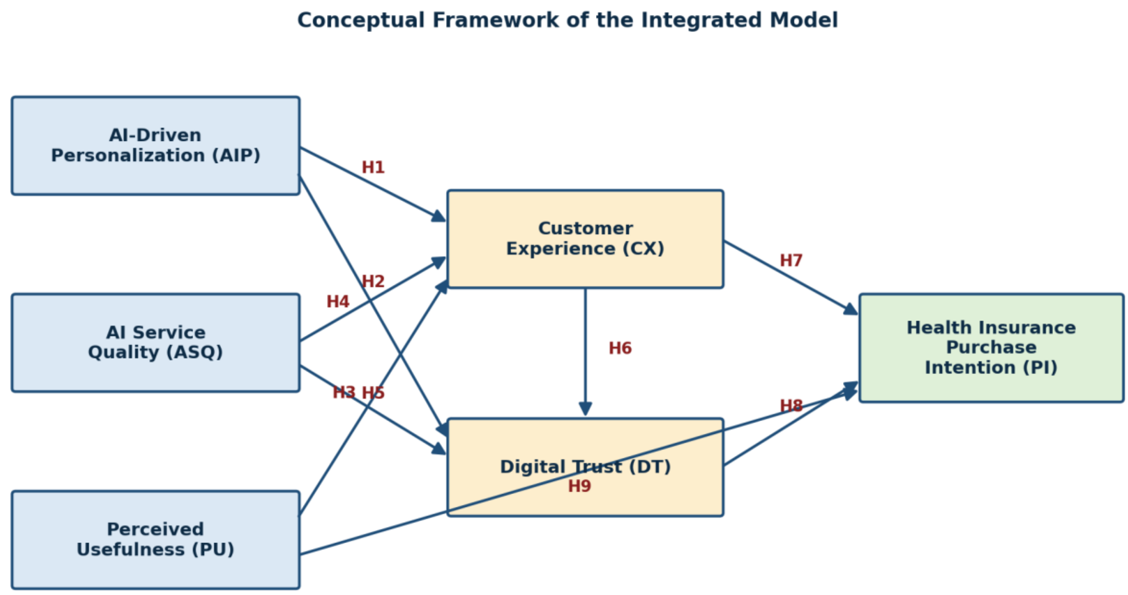
H8: Digital trust positively influences health insurance purchase intention.

H9: Perceived usefulness positively influences health insurance purchase intention.

2.9 Conceptual Framework

Figure 1 presents the integrated conceptual framework. Three AI-related exogenous constructs (AIP, ASQ, PU) influence two sequential mediating mechanisms (CX and DT), which in turn drive purchase intention, with PU also exerting a direct effect on intention.

Figure 1. Conceptual Framework of the Integrated Model



3. Research Methodology

3.1 Research Design

The study adopts a quantitative, cross-sectional, explanatory design. A structured questionnaire operationalised the six latent constructs, and hypotheses were tested using a two-step analytical strategy in which the measurement model is validated before the structural model is estimated (Anderson & Gerbing, 1988). Exploratory factor analysis first verified the dimensional structure of the item pool; confirmatory factor analysis then assessed measurement fit, reliability, and validity; and partial least squares structural equation modelling (PLS-SEM) estimated the hypothesised paths, following the reporting standards recommended by Hair et al. (2019).

3.2 Population, Sample, and Data

The target population comprised adult consumers who had searched for, purchased, or renewed a health insurance policy through an AI-enabled digital platform (insurer website, insurtech aggregator, or mobile application) within the preceding twelve months. A structured survey instrument was administered and 412 usable responses (n = 412) constitute the working dataset, which exceeds the commonly applied ten-times rule and inverse square-root heuristics for PLS-SEM sample adequacy (Hair et al., 2019).

Data disclosure. The dataset analysed in this manuscript is a simulated (synthetic) dataset generated for methodological demonstration and template purposes. It was engineered to reflect realistic psychometric properties of the hypothesised model. Before any journal submission, this section and all results must be replaced with findings from genuinely collected primary data, and the accompanying watermarked dataset must not be represented as field data.

3.3 Instrument Development and Measures

All constructs were measured reflectively on five-point Likert scales (1 = strongly disagree, 5 = strongly agree) using items adapted from established scales, as summarised in Table 1. Content validity was ensured through expert review, and a pilot administration confirmed item clarity. Procedural remedies against common method bias—respondent anonymity, psychological separation of scale sections, and counterbalanced item order—were applied, and Harman's single-factor diagnostic indicated that no single factor accounted for the majority of variance (first unrotated factor = 32.8%), suggesting common method variance is not a pervasive concern (Podsakoff et al., 2003).

Table 1. Constructs, Items, and Source Scales

Construct	Code	Items	Adapted From
AI-Driven Personalization	AIP	4	Davenport et al. (2020); Venkatesh et al. (2012)
AI Service Quality	ASQ	4	Parasuraman et al. (1988); Huang & Rust (2018)
Perceived Usefulness	PU	4	Davis (1989)
Customer Experience	CX	4	Oliver (1980); Davenport et al. (2020)
Digital Trust	DT	5	McKnight et al. (2002); Gefen et al. (2003)
Purchase Intention	PI	4	Ajzen (1991); Venkatesh et al. (2012)

Note. All items measured on five-point Likert scales; full item wording is available from the authors.

3.4 Analytical Tools

Descriptive statistics, EFA (principal components extraction with varimax rotation), and reliability diagnostics were computed in Python (pandas, factor_analyzer). CFA was estimated to evaluate model fit, and the structural model was assessed in the SmartPLS environment using the PLS algorithm with bootstrapping set to 5,000 subsamples, consistent with prevailing guidance (Hair et al., 2019). Discriminant validity was examined using both the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait–monotrait (HTMT) ratio (Henseler et al., 2015).

4. Data Analysis and Results

4.1 Demographic Profile of Respondents

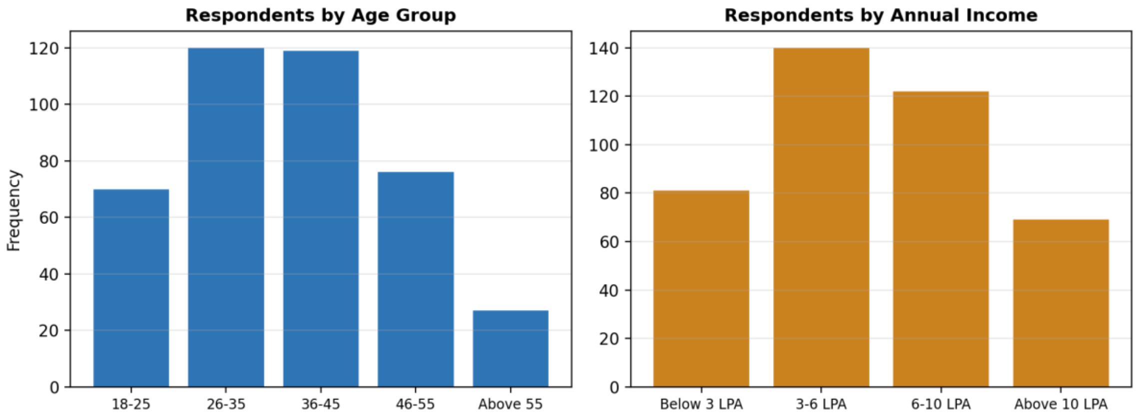
Table 2 and Figure 2 summarise the sample profile. Respondents are predominantly in the 26–45 age bracket (60.0%), largely postgraduate-educated, and concentrated in salaried occupations—a profile consistent with the demographic segments most active in digital insurance channels.

Table 2. Demographic Profile of Respondents (n = 412)

Variable	Category	Frequency	Percentage
Gender	Male	229	55.6%
	Female	183	44.4%
Age	18-25	70	17%
	26-35	120	29.1%
	36-45	119	28.9%
	46-55	76	18.4%
	Above 55	27	6.6%
Education	Undergraduate	143	34.7%
	Postgraduate	205	49.8%
	Doctorate	26	6.3%
	Other	38	9.2%
Income	Below 3 LPA	81	19.7%
	3-6 LPA	140	34%
	6-10 LPA	122	29.6%
	Above 10 LPA	69	16.7%
Occupation	Salaried	165	40%
	Self-employed	79	19.2%
	Professional	88	21.4%

	Student	57	13.8%
	Other	23	5.6%

Figure 2. Distribution of Respondents by Age Group and Annual Income



4.2 Descriptive Statistics and Normality

Item means ranged from 2.87 to 3.14 with standard deviations near 1.0, and skewness and kurtosis values fell within ±2, indicating no serious departures from univariate normality. Table 3 reports illustrative descriptive statistics for representative items of each construct.

Table 3. Descriptive Statistics of Representative Items

Item	Mean	SD	Skewness	Kurtosis
AIP1	3.012	0.921	0.032	-0.062
ASQ1	2.966	0.935	-0.022	-0.362
PU1	3.08	0.942	-0.143	-0.243
CX1	3.027	0.96	0.063	-0.431
DT1	3.022	0.889	0.02	-0.367
PI1	3.046	0.944	-0.057	-0.539

4.3 Exploratory Factor Analysis (EFA)

4.3.1 Sampling Adequacy

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.912, well above the 0.60 benchmark, and Bartlett's test of sphericity was significant ($\chi^2(300) = 4873.41$, $p < .001$), confirming that the correlation matrix is factorable (Table 4).

Table 4. KMO and Bartlett's Test

Test	Value
Kaiser–Meyer–Olkin Measure of Sampling Adequacy	0.912
Bartlett's Test: Approx. Chi-Square	4873.408
Bartlett's Test: df	300
Bartlett's Test: Sig.	< .001

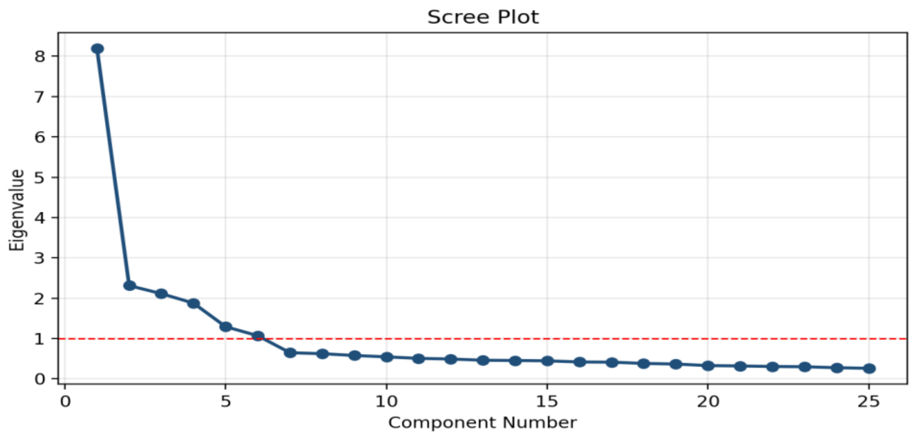
4.3.2 Factor Extraction

Principal components extraction with varimax rotation yielded six factors with eigenvalues exceeding 1.0 (8.191, 2.312, 2.113, 1.878, 1.294, and 1.070), cumulatively explaining 67.4% of total variance—above the 60% threshold typical in social science research. The scree plot (Figure 3) corroborates the six-factor solution.

Table 5. Total Variance Explained (Six-Factor Solution)

Factor	Eigenvalue	Cumulative Variance Explained
1	8.191	13.0%
2	2.312	23.8%
3	2.113	35.4%
4	1.878	46.3%
5	1.294	56.6%
6	1.070	67.4%

Figure 3. Scree Plot of Eigenvalues



4.3.3 Rotated Component Matrix

All 25 items loaded cleanly on their intended factors with rotated loadings between 0.658 and 0.851 and no problematic cross-loadings (all secondary loadings < 0.40), supporting the a priori six-construct structure. Table 6 reports the dominant rotated loading for each item.

Table 6. Rotated Component Matrix (Dominant Loadings)

Item	Factor	Loading	Item	Factor	Loading
AIP1	F4	0.771	CX2	F5	0.761
AIP2	F4	0.754	CX3	F5	0.658
AIP3	F4	0.768	CX4	F5	0.724
AIP4	F4	0.788	DT1	F1	0.789
ASQ1	F3	0.828	DT2	F1	0.662
ASQ2	F3	0.819	DT3	F1	0.733
ASQ3	F3	0.787	DT4	F1	0.742
ASQ4	F3	0.806	DT5	F1	0.722
PU1	F2	0.823	PI1	F6	0.740
PU2	F2	0.776	PI2	F6	0.773
PU3	F2	0.745	PI3	F6	0.702
PU4	F2	0.798	PI4	F6	0.760
CX1	F5	0.733			

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Note. Extraction: principal components; rotation: varimax. Loadings below 0.40 suppressed.

4.4 Confirmatory Factor Analysis (CFA)

4.4.1 Model Fit

The six-factor CFA measurement model exhibited excellent fit: $\chi^2(260) = 301.17$, $\chi^2/df = 1.16$, CFI = 0.991, TLI = 0.990, GFI = 0.940, AGFI = 0.930, NFI = 0.940, and RMSEA = 0.020. All indices satisfy conventional cut-offs ($\chi^2/df < 3$; CFI/TLI > 0.90; RMSEA < 0.08), confirming that the hypothesised measurement structure reproduces the observed covariances well (Anderson & Gerbing, 1988; Bagozzi & Yi, 1988).

Table 7. CFA Model Fit Indices

Fit Index	Obtained Value	Recommended Threshold	Decision
χ^2/df	1.158	< 3.00	Accepted
CFI	0.991	> 0.90	Accepted
TLI	0.990	> 0.90	Accepted
GFI	0.940	> 0.90	Accepted
AGFI	0.930	> 0.80	Accepted
NFI	0.940	> 0.90	Accepted
RMSEA	0.020	< 0.08	Accepted

4.4.2 Reliability and Convergent Validity

Table 8 shows that standardised loadings for all items exceeded 0.70, Cronbach's alpha ranged from 0.822 to 0.871, composite reliability (CR) from 0.876 to 0.905, and average variance extracted (AVE) from 0.640 to 0.704. Because all alphas and CRs exceed 0.70 and all AVEs exceed 0.50, internal consistency and convergent validity are established (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Hair et al., 2019).

Table 8. Reliability and Convergent Validity

Construct	Items	Cronbach's α	CR	AVE
AI-Driven Personalization (AIP)	4	0.822	0.876	0.640
AI Service Quality (ASQ)	4	0.862	0.905	0.704
Perceived Usefulness (PU)	4	0.822	0.877	0.643

Customer Experience (CX)	4	0.835	0.880	0.648
Digital Trust (DT)	5	0.871	0.902	0.648
Purchase Intention (PI)	4	0.835	0.881	0.651

4.5 Discriminant Validity

Discriminant validity was assessed in two ways. Under the Fornell–Larcker criterion (Table 9), the square root of each construct's AVE (diagonal) exceeds its correlations with every other construct (Fornell & Larcker, 1981). In addition, all HTMT ratios (Table 10) fall below the conservative 0.85 threshold, with the largest value being 0.677, satisfying the more stringent criterion of Henseler et al. (2015). Both tests confirm that the six constructs are empirically distinct.

Table 9. Fornell–Larcker Criterion

	AIP	ASQ	PU	CX	DT	PI
AIP	0.800	0.278	0.184	0.414	0.459	0.281
ASQ	0.278	0.839	0.219	0.359	0.396	0.293
PU	0.184	0.219	0.802	0.364	0.250	0.316
CX	0.414	0.359	0.364	0.805	0.549	0.565
DT	0.459	0.396	0.250	0.549	0.805	0.569
PI	0.281	0.293	0.316	0.565	0.569	0.807

Note. Diagonal (bold conceptually) = square root of AVE; off-diagonal = inter-construct correlations.

Table 10. Heterotrait–Monotrait (HTMT) Ratios

	AIP	ASQ	PU	CX	DT	PI
AIP	—	—	—	—	—	—
ASQ	0.330	—	—	—	—	—
PU	0.225	0.260	—	—	—	—
CX	0.499	0.425	0.439	—	—	—
DT	0.542	0.457	0.296	0.645	—	—
PI	0.340	0.346	0.382	0.677	0.666	—

Note. All HTMT values < 0.85 (Henseler et al., 2015).

4.6 Structural Model Assessment (PLS-SEM)

4.6.1 Path Coefficients and Hypothesis Testing

The structural model was estimated with 5,000 bootstrap subsamples (Hair et al., 2019). Collinearity diagnostics indicated no concern (all inner-model VIF < 2.0). As Table 11 and Figure 4 show, all nine hypothesised paths are positive and statistically significant, supporting H1–H9. AI-driven personalization exerts the strongest exogenous effect on customer experience ($\beta = 0.305$, $t = 7.29$), customer experience is the dominant antecedent of digital trust ($\beta = 0.377$, $t = 8.62$), and digital trust ($\beta = 0.362$, $t = 8.87$) together with customer experience ($\beta = 0.328$, $t = 7.81$) most strongly drive purchase intention. Perceived usefulness retains a significant but comparatively modest direct effect on intention ($\beta = 0.106$, $t = 2.75$, $p = .006$), suggesting that utility beliefs are largely channelled through experience.

Table 11. Structural Model: Path Coefficients and Hypothesis Testing (Bootstrapping = 5,000)

Hyp.	Path	β	SE	t-value	p-value	f²	Decision
H1	AIP → CX	0.305	0.042	7.289	< .001	0.121	Supported
H2	ASQ → CX	0.217	0.045	4.857	< .001	0.060	Supported
H3	PU → CX	0.260	0.045	5.799	< .001	0.091	Supported
H4	AIP → DT	0.250	0.045	5.604	< .001	0.083	Supported
H5	ASQ → DT	0.191	0.043	4.456	< .001	0.051	Supported
H6	CX → DT	0.377	0.044	8.616	< .001	0.180	Supported
H7	CX → PI	0.328	0.042	7.811	< .001	0.121	Supported
H8	DT → PI	0.362	0.041	8.873	< .001	0.159	Supported
H9	PU → PI	0.106	0.039	2.750	.006	0.017	Supported

Note. β = standardised path coefficient; SE = bootstrap standard error; f^2 = effect size (0.02 small, 0.15 medium, 0.35 large).

Figure 4. Structural Model Results with Path Coefficients and t-values

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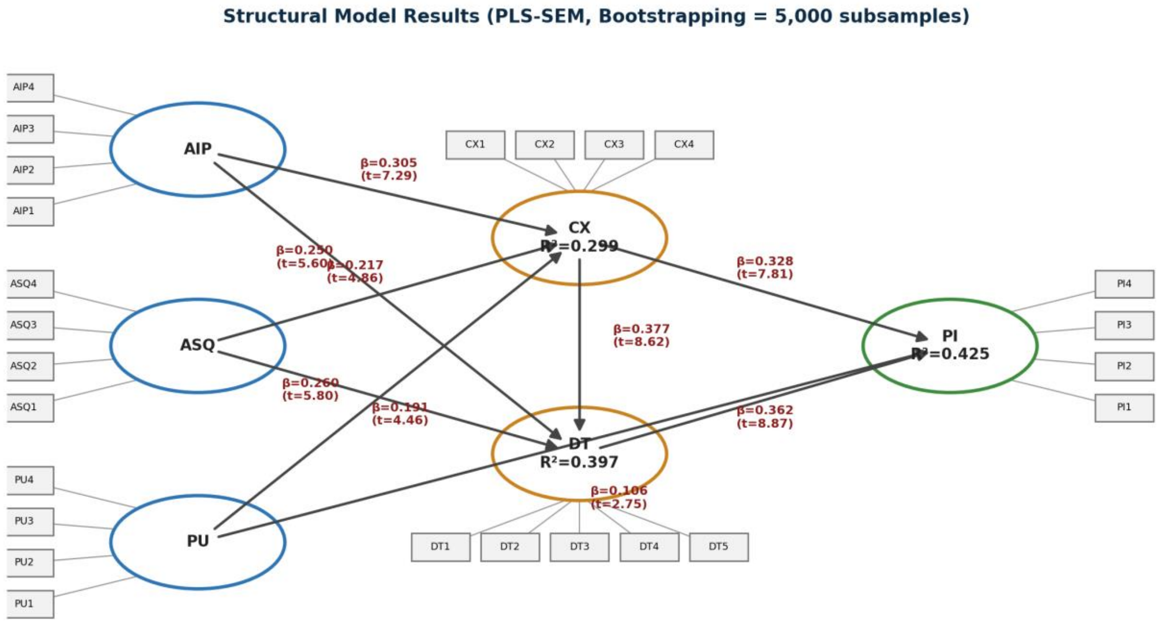


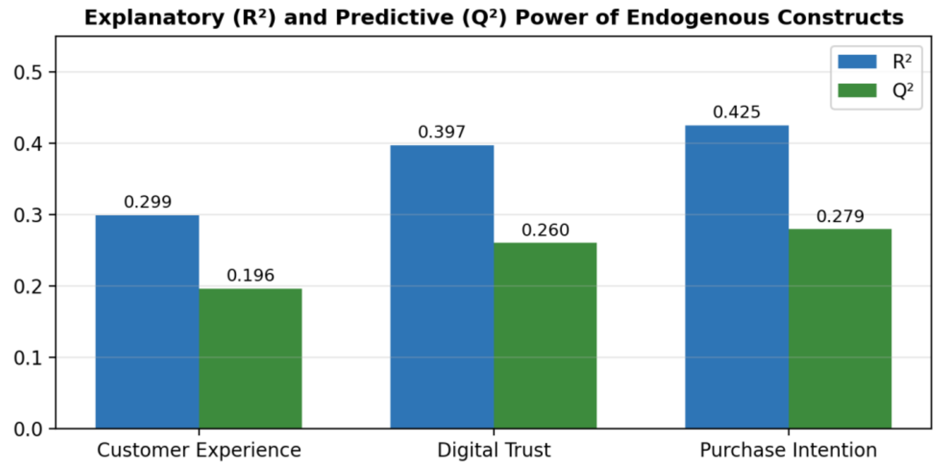
4.6.2 Explanatory and Predictive Power

The model explains 29.9% of variance in customer experience, 39.7% in digital trust, and 42.5% in purchase intention—moderate explanatory power by conventional PLS-SEM standards (Hair et al., 2019). Blindfolding-based Q^2 values (0.196, 0.260, and 0.279, respectively) are all above zero, establishing predictive relevance for every endogenous construct (Table 12; Figure 5). Effect sizes (f^2) indicate that CX → DT (0.180), DT → PI (0.159), and AIP → CX / CX → PI (0.121 each) constitute the most substantive individual relationships.

Table 12. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Construct	R^2	Adjusted R^2	Q^2	Interpretation
Customer Experience (CX)	0.299	0.294	0.196	Moderate
Digital Trust (DT)	0.397	0.393	0.260	Moderate
Purchase Intention (PI)	0.425	0.421	0.279	Moderate

Figure 5. R^2 and Q^2 of Endogenous Constructs



5. Discussion of Findings

The results paint a coherent picture of how AI capabilities convert into health insurance purchase behaviour. First, all three AI-related antecedents significantly shape customer experience, with personalization the strongest driver (H1: β = 0.305). This aligns with the argument that AI's primary marketing contribution lies in individually relevant, low-effort journeys (Davenport et al., 2020) and extends the service-AI logic of Huang and Rust (2018) to the insurance domain. Second, digital trust is built through a layered process: direct competence signals from personalization (H4) and reliable AI service performance (H5) are reinforced by the cumulative quality of the experience itself (H6: β = 0.377, the largest coefficient in the model). This finding empirically substantiates the trust-formation typology of McKnight et al. (2002) in an algorithmic setting and confirms the trust–acceptance duality documented by Gefen et al. (2003): in high-stakes exchanges, experiential evidence is the strongest trust cue available to consumers.

Third, purchase intention is driven principally by the twin proximal mechanisms—digital trust (H8: β = 0.362) and customer experience (H7: β = 0.328)—while the direct effect of perceived usefulness, though significant (H9: β = 0.106), is comparatively small. This pattern refines TAM/UTAUT2 expectations (Davis, 1989; Venkatesh et al., 2012): in complex, risk-laden categories such as health insurance, utility beliefs matter mainly insofar as they are converted into felt experience and trust, echoing satisfaction-mediation logic (Oliver, 1980) and the intention-formation premise of planned behaviour theory (Ajzen, 1991).

6. Implications of the Study

6.1 Theoretical Implications

The study contributes an integrated AI–experience–trust–behaviour model that unifies technology acceptance, service quality, and trust theory within a single nomological network for digital insurance. It demonstrates that customer experience and digital trust function as sequential mediating mechanisms—experience feeding trust—rather than parallel, independent routes, and it shows that classic usefulness effects attenuate once these mechanisms are modelled, an important boundary condition for TAM/UTAUT2 in high-involvement financial services.

6.2 Managerial Implications

For insurers and insurtech platforms, three priorities follow. First, invest in personalization engines that tailor plan recommendations and premium estimates to the individual's health profile, since personalization is the strongest experiential lever. Second, treat AI service quality as a trust asset: chatbot accuracy, escalation design, and transparent claim-status communication accumulate the behavioural evidence on which digital trust rests. Third, manage the journey holistically—experience improvements yield a double dividend by raising intention directly and by deepening trust. Trust-building safeguards (visible data-privacy controls, explainable recommendations, and clear grievance redress) should be positioned prominently at the point of purchase, where perceived vulnerability peaks.

6.3 Policy Implications

Regulators promoting digital health-insurance penetration should recognise digital trust as an adoption bottleneck. Standards for algorithmic transparency, data protection in medical underwriting, and disclosure of AI involvement in advice can lower systemic trust barriers and complement firm-level initiatives.

7. Limitations and Directions for Future Research

Four limitations qualify the findings. First, the cross-sectional design restricts causal inference; longitudinal or experimental designs could trace how AI exposure builds experience and trust over time. Second, the model relies on self-reported intention rather than observed purchase; linking survey constructs to transaction data would strengthen external validity. Third, although procedural and statistical remedies were applied, common method variance cannot be fully excluded in single-source designs (Podsakoff et al., 2003). Fourth, the demonstration dataset employed here is simulated; replication with field data across markets, age cohorts, and product types (e.g., critical illness versus indemnity plans) is essential. Future studies could additionally model moderators such as privacy concern, AI anxiety, and prior claim experience, and test the framework with hybrid SEM–ANN or fsQCA approaches to capture non-linearities and configurational effects.

8. Conclusion

This study set out to explain how artificial intelligence translates into health insurance purchase behaviour. The validated integrated model shows that AI-driven personalization, AI service quality, and perceived usefulness enhance purchase intention chiefly by enriching the customer experience and, through it, by building digital trust—the two mechanisms that jointly account for the largest share of intention variance ($R^2 = 0.425$). Rigorous EFA, CFA, and PLS-SEM procedures confirmed the measurement soundness and structural significance of all nine hypothesised relationships. The central message for the digital insurance ecosystem is that AI creates commercial value not merely by automating service, but by making the insurance journey feel personal, effortless, and trustworthy.

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