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Digital Transformation and Customer Decision-Making in Insurance: A Review of Digital Touchpoints, Trust, and Intelligent Service

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Abstract:

Digital transformation is changing insurance from a product-centred business into a data-intensive, continuously connected service ecosystem. This article reviews how research has conceptualised and investigated the relationship between digital transformation and customer decision-making in insurance, with particular attention to digital touchpoints, trust, and intelligent service. A bibliometric-informed review design is used to integrate performance evidence, science-mapping findings, and customer-level empirical studies. The literature shows a rapid expansion of insurtech research after 2017 and a movement from technology description toward questions of adoption, customer experience, governance, personalisation, and algorithmic accountability. Three interdependent knowledge domains emerge. The first concerns the digital infrastructure of insurance, including artificial intelligence, machine learning, big data, Internet of Things devices, telematics, blockchain, mobile applications, and conversational agents. The second concerns the customer journey, in which perceived usefulness, information quality, convenience, personalisation, and service continuity shape evaluations across multiple touchpoints. The third concerns trust, privacy, perceived risk, fairness, explainability, and human involvement, which determine whether technology-enabled value propositions become actual behavioural intentions. The review identifies a fragmented evidence base, excessive reliance on cross-sectional survey and structural-equation designs, limited longitudinal and cross-cultural research, and weak integration between technology adoption theory and insurance-specific decision processes. A research agenda is proposed around longitudinal customer journeys, hybrid human–AI service, explainable personalisation, fairness, vulnerable consumers, and causal identification. The article also specifies reporting requirements for future Scopus-based bibliometric studies and clarifies why bibliometric mapping must be followed by theory-led interpretation.

Keywords: Digital Transformation; Insurance; Insurtech; Customer Decision-Making; Digital Touchpoints; Trust; Artificial Intelligence; Intelligent Service; Bibliometric Review; Customer Experience

1. Introduction

Insurance is undergoing a structural transformation in which digital technologies increasingly mediate how customers search for information, compare policies, receive advice, purchase coverage, manage claims, and evaluate relationships with providers. The change is broader than the introduction of online sales channels. It involves the redesign of value propositions, data flows, risk assessment, service encounters, organisational capabilities, and regulatory relationships. Research on digital transformation similarly treats the phenomenon as a multidimensional change affecting firms, consumers, and society rather than as the isolated adoption of a single technology. A multidisciplinary review identifies the Internet of Things, social media, mobile applications, artificial intelligence, immersive technologies, and corporate digital responsibility as related domains that can alter consumer decisions and organisational adaptation (Paul et al., 2024).

The insurance context makes customer decision-making especially significant. Insurance is an intangible and often complex service. The customer pays for contingent protection whose value may be realised only after an uncertain future event. Information asymmetry, low purchase frequency, technical language, perceived vulnerability, and uncertainty about claims therefore influence the customer journey. Digital platforms can reduce search and transaction costs, improve information availability, and personalise recommendations. They can also introduce new uncertainty about data use, automated pricing, algorithmic fairness, surveillance, cybersecurity, and the possibility of receiving a decision without meaningful human explanation. The same digital touchpoint can therefore increase convenience while weakening confidence.

Recent studies suggest that insurance research has moved rapidly toward insurtech, artificial intelligence, machine learning, big data, Internet of Things applications, and blockchain. A Scopus-based bibliometric study of 175 InsurTech publications reports a marked increase in output since 2017 and identifies insurance big data and the theoretical relationship between technology and the insurance contract as an unresolved research opportunity (Shamsuddin et al., 2023). Another bibliometric study describes an upward trend in insurtech production and maps co-authorship, co-citation, keyword co-occurrence, citation networks, and country collaboration using Biblioshiny, VOSviewer, and CiteSpace (John et al., 2024). At the wider banking, financial services, and insurance level, a PRISMA-based review screened 39,498 records and retained 1,045 articles, with nine clusters covering areas such as fintech, risk management, anti-money laundering, and actuarial science (Pattnaik et al., 2023). These studies establish the scale and technological breadth of the field, but they do not by themselves explain how customers make decisions within digital insurance ecosystems.

Customer-level studies provide the missing layer. Research on private insurance web areas, based on 4,178 registered customers, finds that perceived digital quality—particularly usefulness, information, and technology—plays a stronger role during online service consumption than prior expectations (Méndez-Aparicio et al., 2020). Research on online insurance trust, based on 606 valid questionnaires, reports positive effects of customisation, core self-evaluation, and information richness on trust; intelligent agents strengthen some, but not all, of these relationships (Wu et al., 2021). A Baltic-market study identifies technology enablers and digital-environment factors across insurance purchase stages while noting the limited theoretical integration of consumer decision-making, information systems, and behavioural economics (Baranauskas & Raišienė, 2021).

The central argument of this article is that digital transformation influences insurance decision-making through a chain of contingent mechanisms rather than through technology adoption alone. Digital touchpoints provide information and interaction; intelligent service converts data into recommendations, automation, and responsiveness; trust determines whether customers accept the resulting service as legitimate and safe; and decision outcomes depend on the alignment between convenience, perceived value, risk, fairness, and human reassurance. A bibliometric approach is useful because it reveals how these themes are distributed across disciplines and how the field has evolved. It is insufficient when used only to count publications or display keyword maps. The mapping must be connected to customer-level evidence and theory.

This article makes four contributions. First, it integrates the insurtech bibliometric literature with empirical research on digital insurance experience, trust, fintech adoption, and intelligent agents. Second, it proposes a three-layer interpretation of the field: digital infrastructure, customer touchpoints, and trust-governed decision outcomes. Third, it compares the methods and limitations used across the relevant literature and identifies where bibliometric findings do and do not support causal claims. Fourth, it develops a research agenda for insurance scholars and practitioners concerned with personalisation, artificial intelligence, chatbots, telematics, fairness, explainability, and hybrid service.

2. Conceptual framing and research questions

2.1 Digital transformation in insurance

Digital transformation should be distinguished from digitisation and digitalisation. Digitisation converts analogue information into digital form. Digitalisation improves an existing process through digital technologies. Digital transformation changes the configuration of processes, capabilities, relationships, and value creation. In insurance, transformation can involve a mobile policy journey, automated underwriting, real-time telematics, predictive claims management, embedded insurance, an AI-enabled contact centre, or a platform that combines comparison, purchase, servicing, and claims. The relevant unit of analysis is therefore the service ecosystem rather than the isolated digital channel.

The literature reflects this expansion. Research on digital service innovation groups the field into innovation for digital servitisation, service innovation in the digital age, and adoption of novel e-services enabled by information-systems development (Rabetino et al., 2023). A broader review of digitalisation in business and management identifies consumer behaviour, digital technologies in financial services, and blockchain as major research tendencies across management, marketing, and finance (Monge & Soriano, 2023). Insurtech research adds industry-specific technologies and concerns, including AI, machine learning, big data, IoT, and blockchain, while also highlighting the need for interdisciplinary collaboration between information technology and economics (Cosma & Rimo, 2024).

Customers encounter digital transformation as a sequence of service propositions and decisions: search, quotation, purchase, assistance, telematics, pricing, and claims. Each encounter produces evidence about competence, transparency, fairness, and control. Digital transformation becomes behaviourally meaningful when these inferences alter search, trust, adoption, purchase, retention, or claim-related behaviour.

2.2 Digital touchpoints and the customer journey

A touchpoint is an interaction between a customer and a provider, brand, intermediary, technology, or other actor in the service ecosystem. Insurance touchpoints include advertising, search engines, comparison platforms, websites, mobile applications, social media, email, online calculators, chatbots, call centres, brokers, connected devices, claims portals, and physical branches. The customer journey is not necessarily linear. A customer may discover a product on social media, compare prices on an aggregator, seek reassurance from a human adviser, purchase through an application, and file a claim through a chatbot. The quality of the journey depends on continuity across these interactions.

Research on device-mediated customer behaviour shows that customer decisions vary according to device characteristics, context of use, screen size, operation mode, and the stage of the journey. The review of 59 articles also reports a lack of comprehensive theories and clear definitions of digital devices in omnichannel environments, together with a need for broader countries, industries, and research designs (Wolf, 2023). This finding is directly relevant to insurance because mobile, desktop, connected-car, wearable, and human-assisted interactions may produce different perceptions of effort, control, privacy, and credibility.

Touchpoints should not be treated as interchangeable. A longitudinal study of 2,970 B2B customers finds that human, digital, and physical touchpoints all contribute to important “moments of truth,” but human and physical touchpoints retain primacy during those encounters (Cambra-Fierro et al., 2024). The study is not insurance-specific and concerns B2B relationships, so its direct generalisation is limited. Its theoretical implication is nevertheless useful: digital availability does not make human reassurance irrelevant. In complex, consequential, or emotionally charged decisions, the value of a digital touchpoint may depend on whether it complements rather than displaces human judgement.

2.3 Trust as a decision mechanism

Trust is a multidimensional expectation that the provider, platform, agent, or algorithm will act competently, reliably, fairly, and in the customer’s interest. In digital insurance, trust may be directed toward the insurer, the intermediary, the platform, the technology, the data process, or the human–machine arrangement. These objects should not be conflated. A customer may trust an insurer’s claims reputation but distrust an opaque pricing algorithm. Another may trust a chatbot for routine information but require a human before accepting a complex policy recommendation.

Trust research in AI indicates that the field has expanded substantially but still suffers from insufficiently contextualised theoretical models and a reliance on exploratory methods (Benk et al., 2024). The implication for insurance is that generic trust scales are unlikely to capture the full decision problem. Insurance trust must address data stewardship, premium fairness, claims credibility, explainability, contestability, and the perceived capacity of the provider to honour a future promise. The technology can be technically accurate while the service remains distrusted if customers cannot understand, challenge, or emotionally accept its decisions.

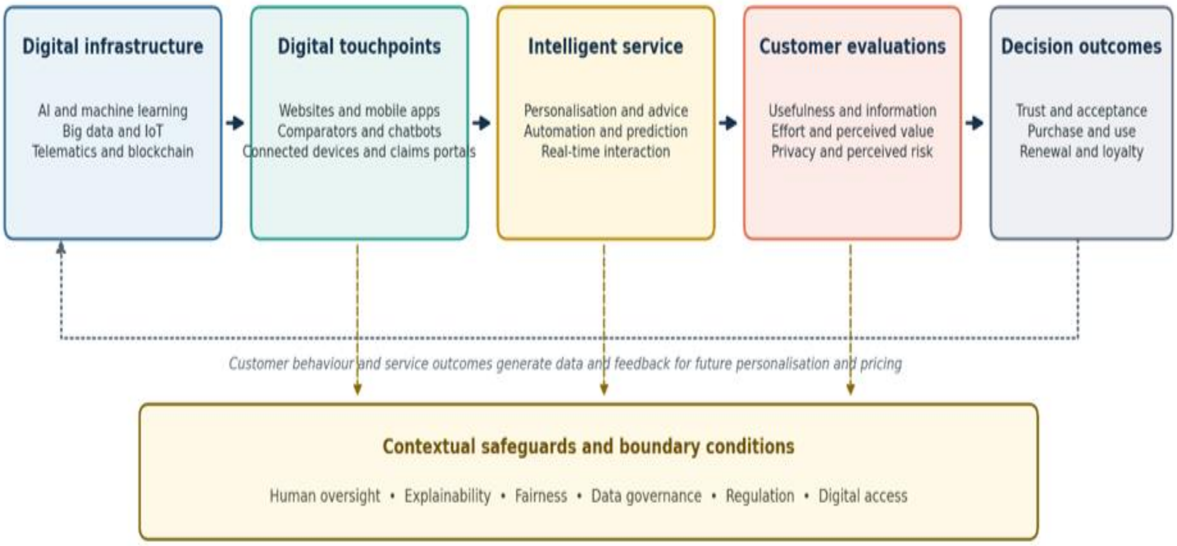
2.4 Intelligent service

Intelligent service refers here to service that uses data, algorithms, AI, automation, or connected devices to sense customer or risk conditions, generate insight, make recommendations, personalise interaction, or execute service actions. It includes chatbots, recommender systems, automated underwriting, predictive claims, telematics, fraud analytics, natural-language interfaces, and AI-supported communication. Intelligence is not equivalent to autonomy. A service may be intelligent because it augments an employee or customer while leaving final responsibility with a human.

The insurance literature documents both the opportunity and the boundary conditions. A review of AI and telematics describes a transition from traditional risk pooling toward usage-based and personalised insurance, enabled by real-time behavioural data from connected vehicles, IoT devices, and wearable sensors. It also identifies privacy, transparency, regulatory compliance, and equitable access as continuing challenges (Sun & Wang, 2025). A review of AI-supported customer communication in insurance identifies trust, perceived usefulness, ease of use, performance expectancy, and personalisation as positive factors, while privacy concerns, creepiness, perceived risk, and effort expectancy are negative factors (Jašková & Kráľová, 2025). Intelligent service therefore changes the decision environment but does not remove the psychological and institutional conditions of acceptance.

Fig. 1: Conceptual framework: digital transformation and customer decision-making in insurance;

A touchpoint–intelligence–trust pathway with contextual safeguards and feedback



Source: Researchers' own based on the available literature

2.5 Research questions

The article addresses four research questions:

RQ1. How has the intellectual and thematic structure of digital transformation and insurtech research developed in relation to insurance customers?

RQ2. How do digital touchpoints influence customer experience and decision-making across the insurance journey?

RQ3. How does trust mediate or moderate the relationship between intelligent service and customer adoption, purchase, use, and loyalty?

RQ4. Which methodological and theoretical gaps should guide future bibliometric and empirical research?

3. Methodology

3.1 Review design

The article uses a bibliometric-informed integrative review. Bibliometric analysis maps the production, intellectual structure, social structure, and conceptual structure of a field. An integrative review then interprets those patterns against substantive empirical evidence. The design follows the logic of bibliometric-systematic review guidance, which recommends combining analysis, synthesis, critical interpretation, and theory development rather than treating a network map as the conclusion of a review (Marzi et al., 2024). It also follows the minimum transparency principles proposed for bibliometric reviews, which organise reporting around the title, abstract, background, methods, results, and discussion and specify 20 reporting items (Montazeri et al., 2023).

The review focuses on research at the intersection of insurance, insurtech, digital transformation, digital service, customer decision-making, trust, AI-enabled service, and related fintech adoption. It includes bibliometric reviews when they provide evidence about the structure or evolution of a research field, and customer-level empirical studies when they explain mechanisms connecting digital service to trust or behaviour. Studies from banking, fintech, and broader service research are used only when their constructs or methods directly illuminate the insurance question. This boundary prevents the review from treating all financial technology research as insurance evidence.

The RStudio bibliometric report referenced in the assignment was not present in the connected materials available for this article. Accordingly, no report-specific sample size, annual production count, keyword frequency, cluster, citation rank, or network statistic is presented as if it came from that report. The numerical values reported below belong to the cited studies that explicitly state them. This distinction is necessary because bibliometric outputs are dependent on database, query, export date, deduplication rules, language restrictions, document types, thresholds, and software settings. A credible Scopus article must not substitute generic or reconstructed values for the author's actual RStudio output.

3.2 Search and eligibility logic

The evidence search used grammatical, self-contained research questions covering three facets: the evolution of insurtech and digital transformation research; customer-level mechanisms involving digital touchpoints, trust, and decision-making; and bibliometric reporting methods. Academic databases available for the review were Semantic Scholar and OpenAlex. The retrieved passages were predominantly abstract-level records. Therefore, methodological details and numerical results are reported only when they were explicitly stated in the retrieved passage.

Eligible records focused directly on insurance, insurtech, digital insurance platforms, insurance fintech, or customer experience; mapped a closely adjacent domain that clarified the insurance field; or measured digital experience, trust, behavioural intention, adoption, or chatbot acceptance. Records were excluded when they described technology without a customer, service, governance, or adoption dimension, or offered no transferable construct. Bibliometric clusters were interpreted as metadata associations, not causal effects on customer behaviour.

3.3 Bibliometric analytical protocol for a Scopus study

A Scopus-based study of the title topic should report the complete search string, fields searched, time window, document types, language limits, subject areas, retrieval date, export format, and inclusion and exclusion decisions. The search string should combine the three conceptual blocks: insurance, digital transformation or touchpoints, and customer decision-making, trust, or intelligent service. Synonyms should include "insurance technology," "InsurTech," "digital insurance," "online insurance," "insurance platform," "customer experience," "customer journey," "trust," "perceived risk," "artificial intelligence," "machine learning," "chatbot," "telematics," "big data," "personalisation," and "usage-based insurance." A narrow query may miss customer studies that use "service quality," "technology acceptance," or "fintech adoption" instead of "digital transformation."

The first processing stage is data audit. Records should be deduplicated by DOI and then reviewed for title, author, source, year, abstract, author keywords, indexed keywords, affiliations, references, and citation counts. Spelling variants and synonyms should be standardised without erasing meaningful distinctions. For example, "AI," "artificial intelligence," and "machine intelligence" may be harmonised for a keyword map, but "chatbot," "conversational agent," and "human–AI service" should be retained as separate concepts when the research question concerns service modality. A thesaurus file should be preserved and reported so that another researcher can reproduce the map.

Performance analysis should report annual production, citations, authors, sources, countries, institutions, collaboration, and highly cited documents, while recognising that visibility is not quality or customer relevance. The 175-record InsurTech study illustrates the value of reporting year, document and source type, subject area, keywords, geography, authorship, and citations together (Shamsuddin et al., 2023). Science mapping should distinguish co-authorship and country networks, co-citation, bibliographic coupling, keyword co-occurrence, thematic maps, and thematic evolution. Insurtech research has combined these techniques with Biblioshiny, VOSviewer, and CiteSpace to examine authors, sources, references, keywords, countries, and trajectories (John et al., 2024). Clusters should be named from actual terms and representative documents, not analyst expectations; they require qualitative reading. B-SLR guidance emphasises critical analysis, coverage, rigour, coherence, timeliness, and originality (Marzi et al., 2024).

4. Evolution and intellectual structure of the field

4.1 From technology adoption to ecosystem transformation

The early and continuing core of the literature is technological. AI, machine learning, big data, IoT, blockchain, and fintech provide the infrastructure through which insurers can change underwriting, pricing, claims, fraud detection, distribution, and customer interaction. The direct insurtech literature consistently portrays the field as expanding. One Scopus study identifies a remarkable increase in InsurTech publications since 2017 (Shamsuddin et al., 2023). Another reports an upward trend in annual scientific production and uses country mappings and collaboration networks to characterise the field’s international and interdisciplinary development (John et al., 2024). A systematic and bibliometric review of insurtech identifies strong attention to AI and blockchain and argues that information technology and economics need to be studied together (Cosma & Rimo, 2024).

The intellectual structure is broader than a technology catalogue. The BFSI AI and machine-learning review identifies nine clusters, including fintech, risk management, anti-money laundering, and actuarial science, after screening 39,498 records and retaining 1,045 articles (Pattnaik et al., 2023). This breadth shows that AI in insurance is connected to operational risk, regulatory compliance, actuarial decision-making, and financial crime, as well as to customer service. Yet the customer is not equally visible in every cluster. Technology and risk clusters can dominate publication output while customer trust, service experience, and contestability remain peripheral. A customer-centred article therefore needs to examine not only whether a technology is studied but also which stage of the insurance value chain and which customer outcome are represented.

Adjacent bibliometric research reinforces this interpretation. A review of AI and customer engagement analysed 190 peer-reviewed articles from 1991 to 2022 and identified ten clusters, connecting AI to marketing, machine learning, and engagement (Suraña-Sánchez & Aramendia-Muneta, 2024). A review of AI adoption based on 91 articles identifies AI, machine learning, TAM, and UTAUT as major themes, but notes that prior research is often limited to specific industries and systems and that adoption theories have been used only to a limited extent (Khanfar et al., 2024). Together, these findings suggest a transition from “what technology does” toward “why and under what conditions customers accept technology.” Insurance research is beginning that transition, but its customer mechanisms remain less consolidated than its technology themes.

4.2 Thematic domains

Three thematic domains organise the evidence.

The first is digital infrastructure and risk intelligence. It includes AI, machine learning, big data, IoT, telematics, blockchain, predictive analytics, and automated decision systems. The dominant question is how insurers can collect, integrate, and analyse data to improve underwriting, pricing, fraud detection, claims, and prevention. The AI–telematics literature describes usage-based and personalised insurance as a movement toward granular, real-time behavioural data and dynamic premium adjustment (Sun & Wang, 2025). The potential customer benefit is better fit, more accurate pricing, and preventive support. The potential customer cost is increased monitoring and uncertainty about whether the data are used fairly.

The second is digital service and customer experience. It includes online self-service, mobile applications, websites, digital quality, information richness, personalisation, conversational agents, and omnichannel continuity.

In private insurance web areas, perceived usefulness, information, and technology are particularly important components of perceived digital quality, and the customer experience is associated with satisfaction (Méndez-Aparicio et al., 2020). In digital service innovation research more broadly, the field spans digital servitisation, service innovation, and e-service adoption, indicating that the customer experience is part of a broader redesign of value creation rather than a cosmetic interface issue (Rabetino et al., 2023).

The third is trust, governance, and responsible intelligence. It includes privacy, security, algorithmic transparency, explainability, fairness, accountability, regulatory compliance, and human oversight. The AI trust bibliometric review identifies a lack of contextualised theoretical models and a reliance on exploratory research (Benk et al., 2024). The insurance AI literature identifies privacy, transparency, compliance, and equitable access as continuing challenges (Sun & Wang, 2025). The chatbot review identifies trust and usefulness as positive acceptance factors but privacy concerns, creepiness, perceived risk, and effort expectancy as negative factors (Jašková & Kráľová, 2025). These findings indicate that customer decision-making is formed at the intersection of service value and institutional legitimacy.

4.3 Geography, collaboration, and disciplinary fragmentation

Digital-finance and AI research is internationally distributed but unevenly concentrated. In digital banking transformation, the United Kingdom, United States, Germany, and China are prominent contributors, while the research base is described as more developed-economy oriented (Osei et al., 2023). A summary of 711 AI and big-data bibliometric reviews from 59 countries describes the United States as most influential by citations and China as most productive by publication count (Thayyib et al., 2023). These patterns should not be translated directly into insurance customer behaviour because country productivity is not customer representativeness.

Insurance markets differ in regulation, distribution, financial literacy, infrastructure, data protection, and broker dependence. Evidence from Bangladesh and the Baltic market shows why national context should be modelled rather than treated as noise (Hassan et al., 2024); (Baranauskas & Raišienė, 2021). The field also remains disciplinary fragmented: information systems contributes acceptance models, marketing contributes customer experience, actuarial research contributes risk and pricing, and governance research contributes fairness and privacy. The reported collaboration between information technology and economics is encouraging, but stronger integration with behavioural economics and consumer psychology is needed (Cosma & Rimo, 2024).

Disciplinary fragmentation is both a strength and a weakness. Information systems research contributes acceptance models and platform studies. Marketing contributes customer experience, engagement, and touchpoint theory. Actuarial and insurance research contributes risk, pricing, underwriting, and claims. Law and governance research contributes fairness, accountability, and privacy. The insurtech literature's reported collaboration between information technology and economics is encouraging (Cosma & Rimo, 2024), but the customer decision problem requires a stronger bridge to behavioural economics, service research, consumer psychology, and insurance regulation.

5. Digital touchpoints and customer decision-making

5.1 Information search and evaluation

Digital touchpoints alter the information stage of insurance decision-making. Websites, comparison tools, mobile applications, calculators, recommendation systems, and social media can increase the volume and speed of available information. However, more information does not automatically produce better decisions. Insurance information is difficult to compare when products use different exclusions, deductibles, limits, waiting periods, definitions, and claim conditions. A digital interface may simplify the display while concealing complexity in the underlying contract.

The customer-experience study of private insurance web areas provides a useful mechanism. Its model, estimated from 4,178 registered customers using partial least squares, finds that expectations matter before web consumption, whereas perceived digital quality—especially usefulness, information, and technology—becomes more important during the service process (Méndez-Aparicio et al., 2020). This suggests that the first decision is not only whether to buy insurance but whether the digital channel is credible and usable enough to support evaluation. Customers may enter with expectations created by advertising or prior experience, but their continuing judgement depends on what the interface actually allows them to understand and do.

Information richness has a dual role. Richer information can reduce uncertainty and strengthen confidence when it is relevant, comprehensible, and traceable. It can also increase cognitive burden when the customer cannot distinguish material terms from promotional content. The online insurance trust study finds that information richness has a positive causal influence on trust in its structural model (Wu et al., 2021). That result supports the value of information, but it does not establish that more information is always better or that the relationship is identical across products and customer groups. Future research should distinguish information quantity from information usefulness, comparability, readability, and decision relevance.

5.2 Personalisation and customisation

Personalisation changes the customer's perception of fit. A recommendation that reflects age, lifestyle, prior coverage, vehicle use, or stated preferences can make insurance appear more relevant and less generic. Customisation allows the customer to select coverage components or adjust limits. In theory, both can reduce search costs and increase perceived value. In practice, personalisation can be experienced as helpful, intrusive, manipulative, or unfair depending on the customer's understanding of data collection and the perceived consequences of the recommendation.

Evidence from online insurance trust supports a positive relationship between customisation and trust, while also showing that intelligent agents do not moderate the customisation–trust relationship in the same way they moderate the relationships involving core self-evaluation and information richness (Wu et al., 2021). This distinction is theoretically important. It suggests that automated intelligence may enhance the interpretation and presentation of information without automatically making a customised offer more trustworthy. Customers may value control over customisation more than the intelligence of the agent that delivers it.

The AI and telematics literature extends personalisation into usage-based insurance. Connected vehicles, wearables, and IoT devices can produce real-time behavioural information and support dynamic premium adjustment or individualised coverage (Sun & Wang, 2025). Such systems shift the decision from a one-time purchase toward an ongoing relationship in which data continuously affect pricing, feedback, prevention, and renewal. The customer decision is therefore partly about accepting a data relationship. The relevant outcomes include not only purchase intention but continued consent, data-sharing willingness, perceived fairness, retention, and willingness to contest a decision.

5.3 Service continuity and omnichannel movement

Insurance customers frequently move among channels. They may begin online, consult a human, return to the application, and later use a claims portal or call centre. A fragmented journey can create repeated authentication, inconsistent information, contradictory recommendations, or an inability to transfer context. These frictions increase effort and may be interpreted as organisational incompetence rather than as a minor interface defect.

The device-mediated behaviour review shows that device characteristics and context influence customer decisions and outcomes and calls for broader validation across industries and countries (Wolf, 2023). The B2B touchpoint study similarly shows cumulative effects on future retention and cross-buying (Cambra-Fierro et al., 2024). The value of an insurance touchpoint therefore depends on its position in the sequence, its relation to other channels, and its effect on future encounters. Continuity affects trust: stable answers and visible human escalation support acceptance, whereas inconsistent information or an untransferable chatbot can increase frustration. Intelligent service should be evaluated at journey level, not only through response accuracy or speed.

5.4 Moments of truth and consequential decisions

Insurance contains high-consequence moments: selecting coverage, disclosing sensitive information, accepting an automated price, reporting a loss, receiving a claim decision, and renewing after a premium change. These moments differ from low-risk service requests because customers evaluate not only convenience but also vulnerability and future protection. The longitudinal touchpoint evidence indicates that human and physical touchpoints remain important during moments of truth even when digital touchpoints contribute to the relationship (Cambra-Fierro et al., 2024).

This finding implies a design principle for insurance: digital transformation should allocate human support according to decision consequence and customer uncertainty. Routine address changes may be fully automated. A complex exclusion, a disputed claim, a vulnerable customer's affordability concern, or a major premium increase may require human explanation and discretion. The appropriate goal is not maximal automation but intelligent allocation of automation and human involvement.

6. Trust, risk, and legitimacy

6.1 Trust in the insurer, platform, and algorithm

Trust should be disaggregated into at least four objects: trust in the insurer, trust in the digital platform, trust in the algorithm or intelligent agent, and trust in data governance. These objects may reinforce one another, but they can also diverge. An established insurer may benefit from brand trust, while a new platform may need to earn trust through transparency and reliable service. A trusted platform may still generate distrust if its pricing model is perceived as discriminatory. A transparent algorithm may not repair a history of poor claims handling.

The online insurance study provides direct evidence that customisation, core self-evaluation, and information richness positively influence trust and that intelligent agents strengthen some relationships (Wu et al., 2021). The study is valuable because it places the intelligent agent inside a trust model rather than treating it as a purely technical tool. Its limitation is that the evidence comes from 606 online questionnaires and structural equation modelling. Cross-sectional self-report data can identify associations and perceived relationships, but they cannot show whether trust persists after a real claim, a premium change, or an adverse automated decision.

The fintech adoption study in Bangladesh likewise shows that trust has a positive moderating role between behavioural intention and actual use (Hassan et al., 2024). This distinction between intention and actual use is important. A customer may intend to use an insurance application because it appears useful, but actual use may depend on security, authentication, availability, perceived control, and trust at the moment of action. Bibliometric studies often foreground intention because it is easy to measure, but insurance research should follow the customer into actual quotation, purchase, renewal, claim, and discontinuation behaviour.

6.2 Privacy and perceived risk

Digital insurance creates a tension between data-intensive value and data-related concern. Telematics and connected devices can support more individualised pricing and prevention, but they also expand the amount, sensitivity, and temporal continuity of customer data. AI-supported communication can make service faster and more available, but customers may worry about surveillance, profiling, secondary use, data breaches, and the inability to opt out without losing service quality.

The review of AI-supported insurance communication identifies privacy concerns, creepiness, perceived risk, and effort expectancy among the negative factors affecting acceptance, alongside trust, usefulness, ease of use, performance expectancy, and personalisation as positive factors (Jašková & Kráľová, 2025). The structure of these findings suggests that trust is not a simple opposite of risk. A customer may trust the insurer's general competence while still perceiving a particular data practice as intrusive. Models should therefore estimate trust, risk, privacy concern, and perceived control as related but distinct constructs.

The AI–telematics review identifies data privacy, algorithmic transparency, regulatory compliance, and equitable access as unresolved challenges (Sun & Wang, 2025). These are not only compliance variables. They are customer decision variables because customers infer whether a policy is fair and whether participation will expose them to penalties they cannot anticipate. A usage-based policy may be attractive to a low-risk customer but unacceptable to a customer who values privacy, lacks access to the required device, or fears that unusual behaviour will be misinterpreted.

6.3 Fairness, explainability, and contestability

Insurance decisions have distributive consequences. A price, eligibility decision, coverage recommendation, fraud flag, or claim outcome can affect affordability and access to protection. When an algorithm makes or supports the decision, customers may seek an explanation that is meaningful rather than merely technical. Explainability should answer at least three questions: what information mattered, how it affected the decision, and what the customer can do if the information is wrong or the outcome is contested.

The AI trust bibliometric review highlights missing perspectives, insufficient contextualisation, and exploratory methods in empirical trust research (Benk et al., 2024). In insurance, contextualisation requires connecting trust to the specific decision and its consequences. Trust in an AI chatbot for a policy address change is not equivalent to trust in an automated claim rejection. The latter requires evidence about procedural justice, explanation, appeal, human review, and the insurer's willingness to correct errors.

A governance study of digital insurance regulation, based on 546 stakeholders across multiple jurisdictions, reports that trust, commitment, and relational factors mediate the relationship between technological capabilities and collaborative governance outcomes. It also argues that digital enablers function as relationship catalysts rather than merely operational tools (Sukma & Yamnill, 2025). This evidence concerns public–private governance rather than individual customers, so it should not be used as direct proof of consumer behaviour. It does, however, support a broader legitimacy perspective: technology produces sustainable outcomes only when embedded in relationships that make accountability and trust visible.

7. Intelligent service in insurance

7.1 Chatbots and conversational agents

Chatbots are among the most visible forms of intelligent service because they directly mediate customer communication. A systematic review of 74 papers examines chatbot performance, acceptance, deployment, applications, methods, samples, and countries, while identifying the need for further research on digital business transformation implications (Miklošík et al., 2021). A more recent insurance-specific study applies UTAUT to policyholders and industry professionals and finds that effort expectancy, social influence, and trust positively affect behavioural intention; the relative importance of the variables differs between ordinary policyholders and professionals (Andrés Sánchez & Gené-Albesa, 2024).

This evidence supports a segmented design. Ordinary policyholders may prioritise ease and low effort because they use chatbots for routine service or because they have limited technical confidence. Professionals may place greater weight on trust and performance expectancy because they understand policy complexity and the consequences of incorrect information. The same chatbot cannot therefore be evaluated through a single average acceptance score. Customer role, expertise, product complexity, and task consequence should be modelled.

Chatbots can also change the emotional character of the journey. They provide immediate availability and may reduce the discomfort of asking basic questions. They may also create a sense of "creepiness" when they appear to know more than the customer expects or when anthropomorphic design suggests a level of understanding the system cannot deliver. The insurance communication review places creepiness alongside privacy concerns and perceived risk as negative factors (Jašková & Kráľová, 2025). Effective design should make the system's identity, capabilities, data access, escalation route, and limitations clear.

7.2 Automated advice and recommendation

Automated recommendations can reduce search costs by matching customers with coverage options. The benefit depends on the quality of the customer data, the completeness of the product catalogue, the transparency of the recommendation logic, and the customer's ability to compare alternatives. An algorithm that recommends a policy without displaying exclusions may increase conversion while weakening informed choice.

Evidence on information richness and intelligent agents suggests that intelligent service is most valuable when it improves information interpretation and usability (Wu et al., 2021). AI should organise complexity, explain trade-offs, and identify questions rather than simply produce a single "best" policy. Robo-advisor research is adjacent, not interchangeable: insurance products contain exclusions, underwriting conditions, and claims contingencies that require product-specific tests of comprehension, risk, and responsibility (Mathew et al., 2024).

7.3 Telematics and usage-based insurance

Telematics transforms insurance from periodic self-reporting toward continuous or event-based data exchange. Vehicle sensors, smartphones, wearables, and connected devices can provide behavioural signals for pricing, prevention, and claims. The AI and telematics review describes real-time data, dynamic premiums, personalised coverage, improved pricing accuracy, reduced adverse selection, fairness perceptions, and preventive risk management as potential benefits, while noting privacy, transparency, compliance, and access concerns (Sun & Wang, 2025).

The customer decision is consequently multidimensional. Customers evaluate the expected price and coverage benefit, the amount of data collected, the possibility of being penalised for anomalous behaviour, the accuracy of the device, the ability to correct the data, and the availability of an appeal. A study that measures only initial adoption intention misses the ongoing consent relationship. Longitudinal research should test whether trust increases when feedback is understandable and prices appear fair, or declines when the data are used in unexpected ways.

Telematics also raises equity issues. If participation requires a compatible vehicle, smartphone, wearable, or stable connectivity, customers without these resources may be excluded from the most attractive products. The equitable-access concern identified in the AI–telematics review (Sun & Wang, 2025) should therefore be linked to actual insurance affordability and availability rather than treated as a general ethical statement.

8. Methodological comparison

The literature is methodologically diverse but uneven in evidentiary strength. Bibliometric reviews are strong for identifying publication growth, disciplinary linkages, influential sources, collaboration patterns, and thematic structures. Surveys and structural equation models are useful for testing relationships among perceived usefulness, trust, information richness, personalisation, behavioural intention, and actual use. Systematic and rapid reviews can consolidate constructs and methods across studies. However, most customer-level evidence remains cross-sectional and self-reported, which limits claims about behaviour over time, causal effects, and service failure.

Table 1 Methodological Comparison

Study or evidence stream	Design and data	Primary focus	Contribution to the present review	Principal limitation
Shamsuddin, Gan, and Anh (2023) (Shamsuddin et al., 2023)	Scopus bibliometric analysis of 175 InsurTech publications	Publication trends, sources, authors, countries, keywords, and citations	Shows growth since 2017 and identifies the need to connect insurance big data with theory and the insurance contract	Maps metadata; does not estimate customer-level causal effects
John et al. (2024) (John et al., 2024)	Scopus bibliometric study using PRISMA, Biblioshiny, VOSviewer, and CiteSpace	AI, machine learning, big data, IoT, blockchain, collaboration, co-citation, and thematic evolution	Demonstrates the interdisciplinary and rapidly evolving structure of insurtech research	Its abstract-level evidence does not establish how mapped themes affect customers
Pattnaik, Ray, and Raman (2023)	PRISMA-based BFSI bibliometric review; 39,498	AI and ML clusters in banking,	Places insurance technology within a broader financial-	BFSI aggregation may conceal insurance-specific

(Pattnaik et al., 2023)	screened and 1,045 included articles	financial services, and insurance	services knowledge structure	customer mechanisms
Méndez-Aparicio et al. (2020) (Méndez-Aparicio et al., 2020)	4,178 registered customers; partial least squares analysis	Digital quality, customer experience, expectations, and satisfaction in private insurance web areas	Shows that usefulness, information, and technology are central to perceived digital experience	Cross-sectional online evidence limits temporal and causal inference
Wu et al. (2021) (Wu et al., 2021)	606 valid online questionnaires; structural equation modelling	Customisation, core self-evaluation, information richness, intelligent agents, and trust	Shows that intelligent agents can moderate some trust relationships but not the customisation–trust relationship	Perceptions and stated relationships may not predict behaviour after real service outcomes
Baranauskas and Raišienė (2021) (Baranauskas & Raišienė, 2021)	Empirical study of the Baltic non-life insurance market	Digitalisation, personalisation, customisation, technology enablers, and purchase decision stages	Connects customer decision-making, information systems, and behavioural economics in a digital insurance context	Market-specific findings require cross-country replication
Hassan et al. (2024) (Hassan et al., 2024)	391 responses; modified UTAUT2 and PLS-SEM in Bangladesh insurance fintech	Effort expectancy, social influence, facilitating conditions, security, innovativeness, trust, intention, and use	Distinguishes behavioural intention from actual use and identifies trust as a moderator	Country, design, and model specification limit transferability
de Andrés Sánchez and Gené-Albesa (2024) (Andrés Sánchez & Gené-Albesa, 2024)	Insurance policyholders and professionals; UTAUT-based structural equation model	Chatbot acceptance, performance expectancy, effort expectancy, social influence, and trust	Shows that acceptance drivers differ between ordinary policyholders and professionals	Acceptance evidence does not equal long-term chatbot performance or claims outcomes
Sun and Wang (2025) (Sun & Wang, 2025)	Review of AI- and telematics-enabled insurance applications	Usage-based insurance, personalised pricing, real-time data, privacy, transparency, compliance, and access	Frames intelligent insurance as an ongoing data relationship rather than a one-time digital purchase	Review-level claims require confirmation through longitudinal customer and market data

Source: Researchers’ own based on the available literature

Table 1, shows that the evidence streams answer different questions. The bibliometric studies establish field development and intellectual structure. The customer studies examine perceived mechanisms, but their outcomes are mainly trust, satisfaction, intention, and acceptance. The literature has much less evidence on actual purchase, renewal, claims, switching, affordability, and long-term data consent. This gap is consequential because insurance is a continuing contract, not a single digital transaction.

8.1 Comparison of bibliometric approaches

Table 2 Bibliometric approaches and Comparison

Analytical approach	What it can show	Relevant evidence	Interpretive caution
Performance analysis	Publication growth, productive authors, sources, countries, institutions, and citations (Shamsuddin et al., 2023)	InsurTech studies report growth and standard indicators such as year, source, author, geography, keywords, and citations	Productivity and citation visibility are not equivalent to customer relevance or methodological quality
Co-authorship and collaboration	Social structure and patterns of institutional or country cooperation (John et al., 2024)	Insurtech research maps author collaboration and country production	Network proximity does not establish substantive intellectual agreement
Co-citation analysis	Intellectual foundations and sources cited together by later publications	Insurtech studies use co-citation to identify influential authors and seminal works	Older, highly cited foundations can dominate and obscure emerging customer research
Bibliographic coupling	Current research fronts based on shared references (Pranajaya et al., 2024)	Financial-inclusion bibliometric research combines coupling, co-citation, co-occurrence, and thematic evolution	Results depend on reference completeness and can split conceptually similar papers with different citation practices
Keyword co-occurrence	Conceptual proximity, dominant terms, and thematic clusters (Pattnaik et al., 2023)	BFSI AI/ML research uses n-gram and co-occurrence analysis to identify nine clusters	Author keywords are inconsistent; a map can reflect terminology choices rather than substantive absence (Omer et al., 2025)
Thematic mapping and evolution	Centrality, density, motor themes, emerging themes, and change across periods (Pranajaya et al., 2024)	Bibliometric reviews use thematic maps and thematic evolution to identify established and emerging areas	Theme labels require qualitative reading of representative documents (Marzi et al., 2024)

Source: Researchers' own based on the available literature

8.2 Methodological strengths and weaknesses

Bibliometrics makes a fragmented field visible across finance, economics, information systems, actuarial science, marketing, and regulation, but a visual cluster can be mistaken for a stable theory. Customer surveys test explicit mechanisms: digital quality relates to experience and satisfaction (Méndez-Aparicio et al., 2020), personalisation-related variables relate to trust (Wu et al., 2021), and acceptance drivers differ between policyholders and professionals (Andrés Sánchez & Gené-Albesa, 2024). Their common weakness is that cross-sectional perceptions may underrepresent actual failures, claims, price changes, and privacy events.

Longitudinal and behavioural designs are necessary. The B2B touchpoint study demonstrates the value of linking touchpoints to moments of truth and later outcomes (Cambra-Fierro et al., 2024). Insurance studies should extend this logic to quotations, purchases, renewals, claims, complaints, appeals, and churn through administrative records, service logs, panels, and field experiments.

9. Research gaps and agenda

9.1 Gap 1: Insufficient integration of bibliometrics and theory

Bibliometric studies identify clusters but often stop before developing a customer-decision theory. The missing bridge is a model explaining how technology-mediated touchpoints change customer beliefs, how beliefs accumulate across the journey, and how trust conditions behaviour. Bibliometric clusters can inform constructs, but the model must be tested through customer and market data. B-SLR guidance calls for theory development beyond descriptive mapping (Marzi et al., 2024).

9.2 Gap 2: Cross-sectional intention dominates actual behaviour

The available empirical studies frequently measure intention, satisfaction, or trust at one point in time. The Bangladesh study is valuable because it distinguishes behavioural intention from actual use and models trust as a moderator (Hassan et al., 2024). The chatbot study examines behavioural intention and differences between policyholders and professionals (Andrés Sánchez & Gené-Albesa, 2024). Yet actual purchase, renewal, switching, claims, complaints, and continued data sharing remain comparatively underdeveloped outcomes in the evidence base.

Future studies should specify the behavioural event and its time horizon. A customer may intend to purchase but abandon a quotation after seeing an exclusion. A customer may buy a telematics policy but discontinue data sharing after a premium increase. A chatbot may receive high satisfaction scores during routine interactions but fail during a claim. These processes require panel data, event histories, field experiments, or linked service records. Longitudinal designs should measure both the customer’s changing beliefs and the objective service outcome.

9.3 Gap 3: Trust is under-contextualised

Trust is often measured as a general attitude toward technology or a platform. The AI trust bibliometric review identifies a lack of contextualised theoretical models and a reliance on exploratory methods (Benk et al., 2024). Insurance requires more specific trust objects and situations. Trust before purchase differs from trust after an automated claim decision. Trust in a chatbot differs from trust in a pricing algorithm. Trust in a provider differs from trust in a data broker or connected-device ecosystem.

Future research should use scenario-specific measures that distinguish competence, integrity, procedural fairness, data stewardship, and contestability. Mixed methods could combine experiments on explanation and human escalation with interviews about fairness and responsibility. Cross-cultural comparisons should test whether transparency, personalisation, and human involvement vary across markets.

9.4 Gap 4: Human–AI complementarity is underdeveloped

The evidence points toward complementarity rather than replacement. Human and physical touchpoints remain important during moments of truth (Cambra-Fierro et al., 2024). Chatbot acceptance depends on trust, effort, social influence, and performance expectancy, with different effects for professionals and ordinary policyholders (Andrés Sánchez & Gené-Albesa, 2024). Intelligent agents moderate some trust relationships but not all (Wu et al., 2021). Future studies should compare human-only, AI-only, visible human escalation, and AI-assisted human configurations across comprehension, fairness, trust, retention, and complaints.

9.5 Gap 5: Personalisation and fairness are rarely studied together

Personalisation is usually presented as a benefit because it increases relevance and may strengthen trust. Telematics and AI can support dynamic pricing and individualised coverage (Sun & Wang, 2025). However, personalisation also creates classification, exclusion, and surveillance risks. The customer may benefit from a lower premium but be unable to understand why the price changed or whether the data are correct.

Research should examine the joint effects of personalisation, perceived control, fairness, and explanation. Experiments can vary whether customers receive a generic price, a personalised price, or a personalised price with an explanation and correction route. Studies should include customers with different levels of digital access and financial literacy. Equity must be measured through outcomes, not only through policy language: access, affordability, error rates, appeal success, and service quality across groups.

9.6 Gap 6: Claims and service recovery are underrepresented

Most digital transformation narratives emphasise acquisition, efficiency, and customer engagement. Insurance trust is tested most severely when the customer makes a claim. The available evidence identifies trust, usefulness, privacy, perceived risk, and human support as important for AI-supported communication (Jašková & Kráľová, 2025), but it does not provide a sufficient longitudinal account of AI-supported claims recovery.

Future studies should treat claims as a central decision environment and examine automated triage, document requests, damage assessment, fraud screening, settlement explanation, and human review. Outcomes should include comprehension, perceived fairness, appeal, retention, recommendation, and subsequent data-sharing behaviour.

9.7 Gap 7: Geographic and market diversity

Bibliometric evidence indicates concentration of digital-finance research in major economies and uneven representation of emerging markets (Osei et al., 2023). Insurance customer evidence from the Baltic market and Bangladesh is valuable precisely because it demonstrates that context matters (Baranauskas & Raišienė, 2021); (Hassan et al., 2024). However, two contexts do not establish a global theory.

Future bibliometric studies should report country coverage transparently and avoid treating country counts as evidence of generalisability. Customer research should include mature insurance markets, emerging markets, rural and urban populations, older customers, financially vulnerable households, and customers with limited digital access. Comparative research should examine how regulation, broker dependence, trust in institutions, financial literacy, and data-protection expectations influence digital adoption.

9.8 Gap 8: Reproducibility and reporting quality

Bibliometric findings are sensitive to search and processing choices. A review of VOSviewer studies identifies dependence on a single database, inconsistent keyword standards, threshold sensitivity, and interpretation as persistent challenges (Omer et al., 2025). The BIBLIO guideline provides a minimum 20-item reporting structure (Montazeri et al., 2023). Future studies should publish the search string, export date, raw-record count, deduplication procedure, thesaurus file, thresholds, software versions, and analysis scripts. This matters because "digital transformation," "insurtech," "AI," "trust," and "intelligent service" are not stable keywords; a narrow query can hide relevant online-insurance, technology-acceptance, customer-experience, or usage-based-insurance research.

10. Implications for theory, practice, and policy

Theoretical implications

The literature supports a customer-decision model in which digital touchpoints are antecedents, intelligent service is a transforming mechanism, trust and perceived risk are evaluative states, and adoption or relationship outcomes are contingent consequences. The model should include feedback: positive encounters can strengthen trust and data-sharing willingness, while negative automated decisions can cause channel switching, complaint, or exit. Customer behaviour also changes the data available for future personalisation and pricing.

This framework extends technology acceptance models by moving beyond perceived usefulness and ease of use. The insurance customer also evaluates contractual meaning, future protection, privacy, fairness, transparency, and the availability of human accountability. The evidence from chatbot acceptance, fintech adoption, online insurance trust, and digital experience supports this extension (Andrés Sánchez & Gené-Albesa, 2024); (Hassan et al., 2024); (Wu et al., 2021); (Méndez-Aparicio et al., 2020).

Managerial implications

Insurers should design digital touchpoints around customer tasks and consequential moments, asking which problem the technology solves, what data it requires, what decision it influences, and how customers can verify or challenge the outcome. Information quality is a trust capability: product comparison should present coverage, exclusions, limits, assumptions, and trade-offs clearly, while personalisation should include data explanations and customer control (Méndez-Aparicio et al., 2020). Human escalation should be visible and empowered for complex products, vulnerable customers, disputed claims, unusual cases, and high-impact pricing decisions (Cambra-Fierro et al., 2024). Dashboards should include trust, comprehension, fairness, complaint escalation, and retention, not only conversion and speed.

Policy implications

Regulators should require clear responsibility for automated insurance decisions. Customers need accessible information about when AI is used, what categories of data are relevant, how errors can be corrected, and how a decision can be reviewed. Governance research in digital insurance emphasises trust, commitment, open data, accountability, and relational mechanisms as conditions for effective digital collaboration (Sukma & Yamnill, 2025). These principles apply to the customer relationship as well as to public–private governance.

Policy should also address equitable access. AI and telematics can create new products and preventive services, but device requirements, connectivity, digital literacy, and data availability may exclude some customers (Sun & Wang, 2025). Consumer protection should therefore assess not only disclosure and consent but also whether digital transformation changes affordability, eligibility, service quality, and appeal outcomes across customer groups.

11. Conclusion

Digital transformation in insurance is best understood as a reconfiguration of customer decision environments, not as a collection of separate technologies. Digital touchpoints expand access and information; intelligent service converts data into personalised interaction and automated action; trust determines whether customers accept the service as competent, fair, safe, and accountable. The three domains are interdependent. A technically advanced service can fail when its information is confusing, its personalisation feels intrusive, or its decisions cannot be explained or challenged.

The bibliometric literature shows a rapidly expanding and interdisciplinary field, while customer-level studies show that perceived digital quality, information richness, personalisation, ease of use, performance expectancy, and trust shape acceptance and experience. The evidence is nevertheless fragmented. Bibliometric maps are stronger at describing intellectual structure than customer outcomes; surveys are stronger at testing perceived relationships than actual behaviour; and cross-sectional studies are weaker than longitudinal or field designs for explaining claims, renewal, data consent, and trust repair.

A Scopus-standard article should combine transparent bibliometric reporting with theory-led interpretation and insurance-specific evidence. Its contribution should be an explanation of how touchpoints, intelligent service, trust, risk, fairness, and human accountability shape decisions across the insurance journey. Future research should prioritise longitudinal customer behaviour, hybrid human–AI service, explainable personalisation, claims and service recovery, cross-market comparison, vulnerable consumers, and reproducible analytical workflows. These priorities can move the field from technology enthusiasm toward evidence-based digital insurance transformation.

Conflict of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

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