

Artificial Intelligence in the Auto Insurance Market: Mechanisms of Empowerment, Consumer Perception, and Developmental Challenges

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Abstract

Artificial intelligence (AI) is reshaping the value chain of the insurance industry, and auto insurance—one of the most important lines in China's property insurance market—has become an active field for AI deployment. Drawing on a literature analysis combined with an online consumer questionnaire, this paper develops a three-dimensional analytical framework linking the value chain, key operational nodes, and corresponding AI technology families, and examines the mechanisms through which AI may empower pricing, claims handling, loss assessment, and anti-fraud activities. The survey retained 260 valid individual responses, among which 165 respondents reported prior experience with AI-enabled auto insurance services. To avoid mixing actual service experience with general expectations, usage-specific satisfaction analyses are conducted primarily among experienced users, while expectation-oriented analyses are conducted on the full sample. The findings show that consumers generally perceive AI-enabled auto insurance services positively: 76.25% of valid claim users are satisfied or very satisfied with claim efficiency, 90.18% of valid loss-assessment users regard AI loss-assessment information as clear or basically clear, and 83.64% of experienced users consider AI risk assessment accurate or comparatively accurate. Nevertheless, documentation burden, communication frictions, insufficient visualisation, weak deep personalisation, and the absence of clear dispute-resolution mechanisms remain salient pain points. At the industry level, data silos, inconsistent loss-assessment standards, product gaps for new energy and intelligent connected vehicles, privacy protection, and organisational change continue to constrain deeper AI adoption. The paper therefore offers mechanism-based and consumer-perception evidence on AI-enabled auto insurance, while recognising that further re-

search using insurer-side operational performance data is needed to establish direct efficiency effects.

Keywords

Artificial Intelligence, Auto Insurance, Smart Pricing, Smart Claims, Anti-Fraud, Consumer Survey

1. Introduction

Auto insurance is a pillar line of China's property insurance market, generating more than 850 billion RMB in premium income in 2023 and accounting for over 50% of total property insurance premiums. As a complex line of business, auto insurance involves an integrated chain of risk management and operational activities spanning underwriting, pricing, claims handling, and risk control [1]. Despite this scale, the segment has long contended with structural challenges: imprecise risk assessment, lengthy claims-handling processes, persistently high fraud incidence, and inadequate product supply for new energy and intelligent connected vehicles. These difficulties compress underwriting margins and constrain insurers' capacity to serve the real economy and consumers.

The rapid maturation of artificial intelligence (AI) technologies offers a new pathway for addressing these long-standing constraints. Advances in machine learning, deep learning, computer vision, natural language processing, and large language models open up the possibility of intelligently reconstructing the auto insurance value chain—from marketing, underwriting, and pricing through to claims, anti-fraud, and customer service. Driven by the national "Internet Plus" agenda and supportive insurance-technology policies, leading Chinese insurers have accelerated AI deployment, generating a rich body of practice.

Existing research has largely concentrated on algorithmic comparisons within isolated segments of the workflow—pricing or fraud detection in particular—and has paid limited attention to an integrated, cross-segment account of how AI empowers the auto insurance value chain. Empirical research that examines AI-enabled auto insurance services from the consumer-perception angle is likewise scarce. Against this backdrop, the paper addresses three interrelated questions: How does AI exert effects on the key nodes of the auto insurance value chain, and what are its underlying mechanisms? How do consumers actually perceive AI-enabled auto insurance services, and what are the principal pain points? What industry-level structural challenges constrain "AI + auto insurance," and how might they be addressed?

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature; Section 3 develops the analytical framework; Section 4 introduces the consumer survey design and sample; Section 5 reports the empirical analysis; Section 6 discusses the structural challenges that persist at the industry level; and Section 7 concludes with policy implications.

2. Literature Review

2.1. International Research

Research on AI in auto insurance abroad has matured along three principal lines: risk assessment and pricing, loss assessment and claims, and fraud detection.

On risk assessment and pricing, Lee and Antonio (2015) [2] compared neural networks, generalised linear models, generalised additive models, and decision trees in predicting claim frequency and reported that neural networks performed best in predictive accuracy. Blier-Wong *et al.* (2020) [3] provided a systematic review of machine learning in property and casualty insurance pricing and reserving, highlighting the integration of unstructured data such as images and geospatial information as a key future direction. Hanafy and Ming (2021) [4] compared logistic regression, XGBoost, Random Forest, decision trees, naïve Bayes, and k-nearest neighbours, and demonstrated the strength of ensemble methods on auto insurance big data.

On loss assessment and claims, Singh *et al.* (2019) [5] developed an end-to-end loss-assessment system that automates damage estimation and claim amount calculation from images of damaged vehicles. Zhang *et al.* (2023) [6] introduced AI-assisted decision-making to facilitate dispute resolution in motor vehicle accident claims through rigorous cost estimation procedures.

On fraud detection and prevention, Aslam *et al.* (2022) [7] constructed an anti-fraud framework combining Boruta-based feature selection with logistic regression, support vector machines, and naïve Bayes; Maiano *et al.* (2023) [8] deployed deep-learning image recognition to verify the authenticity of claim images, contributing a multimodal pipeline for fraud detection.

2.2. Domestic Research

Domestic research has tracked international frontiers but with comparatively few empirical studies. On pricing, Meng *et al.* (2017) [9] demonstrated the effectiveness of support vector machines, gradient boosting trees, and multilayer perceptrons in predicting claim probabilities and aggregate payouts in auto insurance. Yan *et al.* (2022) [10] showed empirically that a GA-XGBoost algorithm outperforms SVM and CART in evaluating UBI driver-behaviour risk.

On loss assessment and claims, Zhou *et al.* (2023) [11] examined the application of insurance technology in claim investigation and loss assessment, proposing a workflow that combines remote guidance with image collection.

On fraud detection, Ye (2011) [12] introduced a hybrid approach combining statistical regression with neural networks for auto-insurance fraud identification; Chen and Li (2022) [13] compared six machine-learning methods and found that gradient-boosting decision trees and Random Forest deliver the best combination of predictive performance and robustness.

2.3. Research Gap and Positioning

Synthesising the existing literature suggests three important gaps. First, both in-

ternational and domestic research has tended to compare algorithms within a single workflow segment, leaving the cross-segment, system-level mechanisms by which AI empowers the auto insurance value chain under-investigated. Second, domestic research is dominated by theoretical analysis and policy recommendations, with relatively limited empirical work; international algorithmic optimisation has, on aggregate, advanced ahead of domestic studies. Third, empirical examination of AI-enabled auto insurance services from the consumer-perception angle remains particularly scarce, leaving the industry's assessment of AI value largely tied to supply-side indicators with insufficient attention to demand-side experience. By integrating literature analysis with 260 consumer questionnaires, this paper engages both supply and demand perspectives and aims to address these gaps.

3. An Analytical Framework for AI-Enabled Auto Insurance

The paper develops a three-dimensional framework, “value chain-key node-AI technology family,” identifying four key nodes along the auto insurance value chain (smart pricing, smart loss assessment, smart claims, and anti-fraud and risk control) and matching each node with the corresponding AI technology family.

3.1. Smart Pricing

Traditional auto insurance pricing rests on historical actuarial data and standard statistical models, which are limited in capturing individual-level behavioural variation and dynamic market conditions. AI—particularly machine learning and deep learning—processes high-volume, high-dimensional data to extract key risk factors such as driving behaviour, vehicle condition, geographic location, and weather conditions, supporting a refined transition from “vehicle-based” to “driver-based” pricing. Usage-based insurance (UBI) models, which adjust premiums dynamically using telematics data, offer a leading example of this paradigm shift. Privacy-preserving computing and federated learning further enable insurers to undertake joint modelling with automakers and third-party platforms without directly exchanging raw data, expanding the data base on which pricing models can draw.

3.2. Smart Loss Assessment

Vehicle damage assessment is the core link in auto insurance claims, directly determining the indemnity amount. Computer vision and deep learning algorithms can process accident-scene photographs or video footage to automatically identify damage location, classify damage type, and assess severity, thereby producing structured repair plans and indemnity recommendations. With pre-trained image recognition models and repair knowledge bases, insurers can complete loss assessment for the great majority of low-amount cases within minutes—an order-of-magnitude improvement over the multi-day cycles typical of traditional workflows. The objectivity of AI recognition also helps to mitigate the information asymmetry and bargaining disadvantage that insurers traditionally face vis-à-vis repair shops

and the insured.

3.3. Smart Claims

Conventional auto-insurance claims involve multiple steps—reporting, inspection, loss assessment, review, payment, and case closure—which are time-consuming, costly, and prone to subjective judgement. AI-driven smart claims systems use NLP to extract structured information from incident reports, computer vision to identify photographic evidence automatically, and workflow automation to connect processing nodes, compressing claims-handling cycle times substantially; for low-amount cases, indemnity payment can be completed within minutes. Blockchain technology contributes tamper-resistant evidence storage, further enhancing process transparency and customer trust.

3.4. Anti-Fraud and Risk Control

Auto insurance fraud is increasingly professionalised, organised, and concealed, and is poorly addressed by traditional manual review and rule-based heuristics. Machine learning models trained on historical claim data identify abnormal claim patterns automatically; combined with NLP for semantic analysis of incident narratives, computer vision for verifying scene photographs, and graph neural networks for detecting collusion among related parties, AI supports a multimodal anti-fraud architecture. Voice-based emotion recognition and biometric identification further enable insurers to detect anomalous emotional states or identity risks at the point of incident reporting, shifting the anti-fraud frontier upstream. AI-driven real-time monitoring and dynamic risk assessment likewise enable insurers to intervene at the early stages of risk accumulation.

Table 1 summarises the four nodes alongside their AI technology families and underlying mechanisms.

Table 1. Key nodes of the AI-enabled auto insurance value chain.

Value-Chain Node	Principal AI Technology Families	Core Mechanism
Smart Pricing	Machine learning, deep learning, telematics-based UBI, privacy-preserving computing and federated learning	Vehicle-to-driver pricing transition; dynamic premiums; multi-source joint modelling
Smart Loss Assessment	Computer vision, deep learning, knowledge graphs	Automated damage identification; structured repair plans; reduced information asymmetry
Smart Claims	Natural language processing, workflow automation, blockchain evidence storage	Minute-level claims; process transparency; auditable evidence chain
Anti-Fraud and Risk Control	Machine learning, graph neural networks, computer vision, voice emotion recognition, biometric identification	Anomaly detection; ring-fraud identification; upstream anti-fraud screening

4. Research Methodology and Data Sources

4.1. Survey Design

To examine the practical effectiveness of AI-enabled auto insurance services from the consumer-perception perspective, this study used an online questionnaire adminis-

tered mainly through the Credamo questionnaire platform, supplemented by dissemination through WeChat groups, WeChat Moments, and online car-owner/insurance-related communities. The target respondents were adult drivers or potential auto-insurance consumers who were able to understand and evaluate AI-enabled auto-insurance services. The questionnaire did not impose a regional restriction and did not collect a separate province/city variable; therefore, the results should be interpreted as online-sample evidence rather than geographically representative national estimates. The instrument contains 18 items covering demographic information, driving experience, prior AI-enabled auto-insurance experience, AI claims, AI loss assessment, AI risk assessment, process-optimisation expectations, and opened personalisation needs. The main questionnaire items and response options are presented in the **Appendix**. Respondents who reported no prior AI-enabled auto-insurance experience were routed directly to expectation-oriented items, thereby separating service-experience evaluation from general demand-side expectations.

4.2. Sample and Data

Table 2. Sample characteristics of valid respondents.

Characteristic	Category	N	Share
Gender	Male	89	34.23%
Gender	Female	171	65.77%
Age	18 - 25	122	46.92%
Age	26 - 35	92	35.38%
Age	36 - 45	31	11.92%
Age	46 - 55	9	3.46%
Age	Over 55	6	2.31%
Driving experience	Less than 1 year	61	23.46%
Driving experience	1 - 3 years	74	28.46%
Driving experience	3 - 5 years	47	18.08%
Driving experience	5 - 10 years	53	20.38%
Driving experience	Over 10 years	25	9.62%
Prior AI-enabled auto insurance experience	Yes	165	63.46%
Prior AI-enabled auto insurance experience	No	95	36.54%

Note: Percentages are calculated using the 260 retained individual responses as the denominator.

A total of 260 valid individual responses were used for the empirical analysis. The sample characteristics are summarised in **Table 2**. Among the 260 retained respondents, 171 were female (65.77%) and 89 were male (34.23%). Respondents were concentrated in the 18 - 25 and 26 - 35 age brackets, and all retained individual responses reported some driving experience. A total of 165 respondents (63.46%) reported having previously used AI-enabled auto-insurance services, while 95 respondents (36.54%) reported no prior use. Since the questionnaire did not collect IP addresses

or province/city information, the data processing did not involve geographic stratification. Data cleaning included: deleting non-individual summary rows, checking completeness of mandatory demographic and screening questions, and applying questionnaire skip logic when defining the analytical sample for each module.

4.3. Analytical Methods

Data analysis combines frequency analysis, mean Likert-score reporting, cross-tabulation, and subgroup comparison. In response to the questionnaire's skip logic, the 95 respondents without prior AI-enabled auto-insurance experience are excluded from usage-specific satisfaction analyses but retained for expectation-oriented items. Consequently, the valid base differs across modules: claim-cycle and claim-efficiency results are calculated among 160 valid claim-experience responses; loss-assessment clarity and transparency are calculated among 163 valid loss-assessment responses; risk-assessment indicators are calculated among 165 experienced users; and process-optimisation expectations are calculated on the full sample of 260 respondents. Likert items were coded so that larger values indicate more positive evaluations. Five-point satisfaction items were coded from 1 = very dissatisfied to 5 = very satisfied; four-point clarity, accuracy, and personalisation items were coded from 1 to 4 in ascending order of positive evaluation. Cronbach's alpha was calculated only for reflective Likert-type blocks with at least two items: the loss-assessment perception block (Q8 and Q9, $\alpha = 0.596$) and the risk-assessment perception block (Q11 - Q13, $\alpha = 0.637$). The claim-efficiency block contains a single satisfaction item and the process-optimisation block consists of multiple-response expectation items; therefore, Cronbach's alpha is not treated as applicable for these two formative or single-item blocks. Mean Likert scores and reliability information for the core survey indicators are reported in **Table 3**. Basic subgroup comparisons were conducted using Welch's t-test for prior-use status and Kruskal-Wallis tests for age and driving-experience groups, with the results presented in **Table 4**. The correspondence between questionnaire items and analytical modules is shown in the **Appendix**.

Table 3. Mean likert scores and reliability information for core survey indicators.

Indicator	Scale	Valid N	Mean	SD	Positive/high share
Claim efficiency satisfaction	1 - 5	160	3.89	0.67	76.25%
Loss-assessment clarity	1 - 4	163	3.08	0.54	90.18%
Loss-assessment transparency satisfaction	1 - 5	163	3.88	0.62	77.91%
Risk-assessment accuracy	1 - 4	165	2.92	0.54	83.64%
Personalised recommendation receipt	1 - 4	165	3.16	0.51	93.94%
Risk-assessment satisfaction	1 - 5	165	3.96	0.61	81.82%

Note: Cronbach's alpha was calculated for reflective multi-item perception blocks. Loss-assessment perception (Q8 - Q9): $\alpha = 0.596$; risk-assessment perception (Q11 - Q13): $\alpha = 0.637$. Cronbach's alpha is not applicable to the single-item claim-efficiency satisfaction indicator or the multiple-response process-optimisation expectation block. Given the exploratory nature of this consumer-perception survey and the limited number of items in some modules, these reliability results should be interpreted with caution. Future studies may improve scale reliability by expanding the number of items in each construct.

Table 4. Basic subgroup comparisons of composite scores.

Composite indicator	Valid N	Mean	SD	Prior-use p	Age p	Driving-experience p
Claims efficiency satisfaction	160	3.89	0.67	N.A.	0.459	0.468
Loss-assessment perception	163	3.83	0.57	N.A.	0.173	0.062
Risk-assessment perception	165	3.80	0.51	N.A.	0.105	0.129
Process-optimisation demand	260	7.32	1.91	p < 0.001	0.048	0.062

Note: Prior-use status is tested only for the process-optimisation demand score because respondents without prior AI-enabled auto-insurance experience skipped usage-specific satisfaction modules. Age and driving-experience comparisons use Kruskal-Wallis tests; prior-use comparison uses Welch's t-test.

5. Empirical Analysis: Consumer Perception of AI-Enabled Auto Insurance

5.1. AI Smart Claims

The claim-related analysis is based on respondents who had relevant AI-claim experience. Among the 160 valid claim-cycle responses, 115 respondents reported that the process from claim submission to indemnity receipt took less than one week, accounting for 71.88%. Claim-efficiency satisfaction is also positive: 122 of the 160 valid respondents selected “satisfied” or “very satisfied”, yielding a positive share of 76.25% and a mean score of 3.89 on a five-point scale. However, pain points remain concentrated in front-end document preparation and process interaction. Specifically, 62.50% of valid claim respondents selected excessive documentation requirements, 48.75% selected communication frictions with insurers, 48.13% selected complex application procedures, and 42.50% selected long review time. These results indicate that AI may have improved back-end processing speed, but the consumer-facing interface of documentation submission, guidance, and communication remains an important bottleneck.

5.2. AI Smart Loss Assessment

For AI smart loss assessment, 147 of the 163 valid respondents regarded the loss-assessment information as clear or basically clear, corresponding to a positive clarity share of 90.18% and a mean clarity score of 3.08 on a four-point scale. Transparency satisfaction is also favourable: 127 of the 163 valid respondents were satisfied or very satisfied, with a mean transparency score of 3.88 on a five-point scale. At the same time, the two most frequently identified shortcomings were the lack of visualisation and unclear dispute-resolution mechanisms, each selected by 60.12% of valid loss-assessment respondents, followed by insufficient detail in loss-assessment reports (42.94%). The results suggest that AI image recognition has reached a relatively high level of perceived usability at the identification stage, but further improvement is needed in explainable presentation and post-assessment dispute handling.

5.3. AI Smart Risk Assessment

Risk-assessment evaluation is based on 165 respondents with prior AI-enabled auto-insurance experience. In total, 138 respondents regarded AI risk assessment

as accurate or comparatively accurate, producing a positive share of 83.64% and a mean score of 2.92 on a four-point scale. In addition, 155 respondents reported receiving personalised suggestions or services at least occasionally, corresponding to 93.94% and a mean score of 3.16 on a four-point scale. Satisfaction with risk-assessment functions is likewise positive: 135 respondents were satisfied or very satisfied, accounting for 81.82%, with a mean score of 3.96 on a five-point scale. Nevertheless, 75.15% of experienced users identified insufficient deep personalisation as a remaining problem, 55.76% reported that risk factors considered by the system were not comprehensive enough, and 44.24% noted untimely updates. These findings imply that consumers recognise the value of AI risk assessment, while expecting richer individual-level modelling and more dynamic feedback.

5.4. Consumer Demand for AI-Driven Process Optimisation

The expectation-oriented items were answered by the full sample of 260 respondents, including both experienced users and non-users. In claims handling, the most frequently selected improvement expectations were faster reporting response (73.08%), online claim guidance (71.92%), accelerated review (67.69%), and automated liability identification (65.38%). In loss assessment, respondents placed the strongest emphasis on more accurate results (81.54%) and real-time assessment at the accident scene (79.62%), followed by support for multiple accident scenarios (66.54%). In risk assessment, improving the timeliness of risk updates was the most salient expectation (81.15%), followed by including more comprehensive risk factors (74.23%) and providing visual and understandable risk reports (71.15%). Sub-group comparisons further show that non-users selected more process-optimisation expectations than experienced users on average (8.14 versus 6.85 selected items out of 10; Welch's t-test $p < 0.001$), suggesting that consumers without prior experience may hold stronger expectations for AI-enabled service improvement.

Table 5. Consumer evaluation of AI-enabled auto insurance and key pain points.

Evaluation Dimension	Positive Share/Main Result	Key Pain Points	Improvement Expectations
AI Smart Claims	76.25% satisfied or very satisfied with claim efficiency (n = 160); 71.88% of valid claim users reported a claim cycle shorter than one week.	Documentation burden 62.50%; communication frictions 48.75%; complex application process 48.13%; long review time 42.50%.	Fast reporting response 73.08%; online claim guidance 71.92%; accelerated review 67.69%; automated liability identification 65.38%.
AI Smart Loss Assessment	90.18% regarded loss-assessment information as clear or basically clear (n = 163); 77.91% were satisfied or very satisfied with transparency.	Lack of visualisation 60.12%; unclear dispute-resolution mechanism 60.12%; insufficient report detail 42.94%.	More accurate loss-assessment results 81.54%; real-time loss assessment 79.62%; support for multiple accident scenarios 66.54%.
AI Smart Risk Assessment	83.64% regarded risk assessment as accurate or comparatively accurate (n = 165); 81.82% were satisfied or very satisfied; 93.94% received personalised suggestions at least occasionally.	Lack of deep personalisation 75.15%; insufficient risk factors 55.76%; untimely result updates 44.24%.	More timely risk updates 81.15%; more comprehensive factors 74.23%; visual and understandable risk reports 71.15%.

Table 5 summarises consumer evaluations of AI-enabled auto-insurance services, the key pain points identified, and the corresponding improvement expectations across the three service dimensions. In aggregate, the results provide demand-side evidence that consumers perceive AI-enabled auto-insurance services positively in terms of efficiency, clarity, accuracy, and personalised recommendation. However, these findings are consumer-perception evidence rather than direct causal evidence from insurer-side operational performance data. Complex operational procedures, cumbersome documentation, insufficient visualisation, weak deep personalisation, and limited timeliness of risk updates remain the principal demand-side concerns and should figure prominently in subsequent technological iterations.

6. Discussion: Structural Challenges in “AI + Auto Insurance”

The consumer survey illuminates the achievements and shortcomings of AI-enabled auto insurance services from the demand side. On the supply side, several structural challenges remain at the industry level. Four warrant particular attention.

6.1. Data Silos and the Difficulty of Multi-Source Data Integration

AI applications in auto insurance depend heavily on multi-source data—telematics, user behaviour, and third-party data—but data formats across automakers, repair shops, and insurers remain non-uniform and cross-platform sharing arrangements are underdeveloped. As parties to the claim, the insured may also answer selectively or omit relevant information during inquiries, further constraining the availability of reliable raw data. The resulting “data silos” limit both the training-sample scale and the cross-scenario generalisation of AI models, representing a foundational bottleneck that the industry must collectively address.

6.2. Difficulty of Standardising Loss Assessment

Vehicle damage assessment is intrinsically heterogeneous: identical damage to the same vehicle model can yield substantially different repair cost estimates depending on location; the same repair shop may price parts and labour differently across vehicle models; and even within identical vehicle-shop pairings, differences in collision angle and force lead to divergent damage profiles. Final pricing typically emerges from negotiation between the repair shop and the insured, with reference to local market rates, leaving the insurer in a comparatively passive position. AI image recognition can improve the objectivity of damage classification, but moving from “assisted recognition” to “unified pricing” requires industry-level standards and underlying data infrastructure beyond the reach of any individual insurer.

6.3. Product Gaps and Pricing Dilemmas for New Energy and Intelligent Connected Vehicles

New energy vehicles increasingly feature a “vehicle-battery separation” model, but

most existing dedicated products bundle the battery within whole-vehicle insurance, leaving stand-alone coverage for batteries or non-battery components underdeveloped. For intelligent connected vehicles, the industry has yet to develop dedicated terms and products and continues to rely on traditional compulsory motor liability and vehicle-damage products. The risk types, liable parties, and rate-making considerations differ markedly across automation levels, and emerging risks such as cybersecurity, data privacy, and safety of intended functionality have no clear counterpart in legacy products. At the same time, high loss ratios for new energy vehicles and high per-incident repair costs for intelligent connected vehicles create a pricing dilemma in which falling accident frequency co-exists with rising repair costs, complicating the application of traditional actuarial models.

6.4. Privacy Protection and Organisational Change

AI-enabled auto insurance relies heavily on the deep utilisation of personal data, but the Personal Information Protection Law and related regulations have raised the bar for data collection, storage, and use, requiring insurers to balance compliance with modelling needs. Internal resistance is also non-trivial: traditional business units may view AI deployment as a substitution threat, with underwriters and field investigators displaying limited adaptability to new technologies. Organisational change therefore constitutes a non-technical but consequential constraint.

Table 6 summarises the four challenges alongside potential AI-enabled responses.

Table 6. Key challenges in “AI + Auto Insurance” and potential pathways.

Key Challenge	Manifestation	Potential AI-Enabled Pathway
Data silos and information loss	Limited cross-firm data sharing; inadequate disclosure by insureds	Federated learning, differential privacy, privacy-preserving multi-party modelling
Non-standard loss assessment	Heterogeneity across vehicle models, locations, parts, and labour rates	Image recognition combined with knowledge graphs to build structured loss-assessment libraries
Product gaps and pricing dilemmas	Vehicle-battery separation; absence of dedicated ICV terms; loss-ratio-cost mismatches	Scenario-specific AI risk assessment supporting product innovation; dynamic actuarial models on telematics and sensor data
Privacy protection and organisational change	Tightening compliance constraints; resistance to traditional-role transformation	Explainable AI (XAI) and human-machine collaborative governance frameworks

7. Conclusions and Policy Implications

Drawing on a literature analysis combined with 260 valid consumer questionnaires, this paper has examined the mechanisms of AI empowerment, consumer perception, and developmental challenges in the auto insurance market from both supply and demand perspectives. Three principal findings stand out. First, AI has the potential to empower smart pricing, smart loss assessment, smart claims, and anti-fraud, each underpinned by a distinct combination of AI technology families and value-creation logics; however, the evidence in this paper is mechanism-based

and perception-based rather than a direct causal test using insurer-side operational performance data. Second, experienced consumers evaluate AI-enabled services positively in terms of claim efficiency, loss-assessment clarity, and risk-assessment accuracy, while also identifying cumbersome documentation, weak visualisation, insufficient deep personalisation, and unclear dispute-resolution mechanisms as key pain points. Third, structural challenges—data silos, loss-assessment standards, product gaps, pricing dilemmas, and concerns over privacy and organisational change—persist at the industry level and lie beyond the reach of any single insurer.

Building on these findings, four policy directions are proposed.

First, deepen cross-stakeholder data sharing and supporting infrastructure. Regulators should take the lead in establishing industry-level anti-fraud databases and structured vehicle loss-assessment knowledge graphs, paired with privacy-preserving computing technologies such as federated learning, so as to expand the data base for model training without compromising compliance.

Second, advance explainable AI (XAI) and human-machine collaborative governance. To address the consumer concerns over weak deep personalisation and communication frictions, insurers should embed explainable AI tools at the core nodes of pricing, loss assessment, and anti-fraud, enabling consumers to understand evaluation logic; clear human-review mechanisms should likewise be established, positioning AI as a productivity tool rather than a substitute and easing organisational resistance.

Third, accelerate the development of dedicated insurance products and contractual terms for new energy and intelligent connected vehicles. Regulators and industry associations should partner with academic and industrial actors to design dedicated terms covering vehicle-battery separation and autonomous-driving liability allocation, while insurers leverage AI-supported actuarial research to develop more targeted product portfolios.

Fourth, encourage industry-academia collaboration and talent cultivation. Insurers should deepen cooperation with universities and technology firms in frontier areas including UBI modelling, image recognition, and graph neural networks, while supporting the cultivation of cross-disciplinary insurance-technology talent to underpin long-term digital transformation.

Several limitations of this study should be acknowledged. First, the sample is an online convenience sample and skews toward younger respondents; moreover, the questionnaire did not collect a province/city variable, so the results should not be interpreted as geographically representative national estimates. Second, the survey captures subjective perceptions and expectations, which may diverge from internal performance metrics held by insurers; cross-validation with proprietary insurer data would be a productive extension. Third, usage-specific satisfaction results are based on experienced users only, while expectation-oriented items use the full sample, so comparisons across modules should be interpreted with attention to their different analytical bases. Fourth, the paper does not differentiate AI

applications across product lines, regions, or insurer types, leaving disaggregated investigations to future research.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix: Main Questionnaire Items

The questionnaire was originally administered in Chinese. The following list presents the main items and response options used in the survey instrument.

Q1 Gender [single choice]: A. Male; B. Female

Q2 Age [single choice]: A. 18 - 25; B. 26 - 35; C. 36 - 45; D. 46 - 55; E. Over 55

Q3 Driving experience [single choice]: A. Less than 1 year; B. 1 - 3 years; C. 3 - 5 years; D. 5 - 10 years; E. Over 10 years

Q4 Have you ever used AI-enabled auto-insurance services? [single choice]: A. Yes; B. No. Respondents selecting "No" were routed to Q15.

Q5 When using AI-enabled auto-insurance claims services, how long did it usually take from claim submission to indemnity receipt? [single choice]: B. 1 - 3 days; C. 3 - 7 days; D. 7 - 15 days; E. More than 15 days; No use.

Q6 Are you satisfied with the current claim efficiency of AI-enabled auto-insurance services? [single choice]: Very satisfied; satisfied; neutral; dissatisfied; very dissatisfied.

Q7 What major problems have you encountered in AI-enabled claims? [multiple choice]: Complex claim application process; excessive documents required; long review time; poor communication with the insurer; other.

Q8 In loss assessment, is the information displayed by AI clear and understandable? [single choice]: Very clear; basically clear; neutral/some parts unclear; not clear; no use.

Q9 Are you satisfied with the transparency of AI-enabled loss assessment? [single choice]: Very satisfied; satisfied; neutral; dissatisfied; very dissatisfied.

Q10 What problems exist in AI-enabled loss assessment? [multiple choice]: Insufficient report detail; lack of visualisation; unclear dispute-resolution mechanism; other.

Q11 How accurate do you think AI-enabled auto-insurance risk assessment is? [single choice]: Very accurate; comparatively accurate; neutral/some bias; not very accurate; no use.

Q12 Have you received personalised suggestions or services based on AI risk-assessment results? [single choice]: Often and helpful; occasionally and somewhat useful; rarely; never.

Q13 Are you satisfied with the current AI-enabled risk-assessment function? [single choice]: Very satisfied; satisfied; neutral; dissatisfied; very dissatisfied.

Q14 What problems remain in the current AI risk-assessment system? [multiple choice]: Risk factors considered are not comprehensive; results are not updated in time; lack of personalised assessment; other.

Q15 Which parts of the claims process should AI further optimise? [multiple choice]: Fast reporting response; automated liability identification; online claim guidance; accelerated review; other.

Q16 What improvements do you expect AI to bring to loss assessment? [multiple choice]: More accurate results; support for multiple accident scenarios; real-time on-site loss assessment; other.

Q17 In risk assessment, what aspects should AI improve? [multiple choice]:
More comprehensive risk factors; timelier risk updates; visual and understandable risk reports; other.

Q18 Do you expect AI to provide other personalised auto-insurance services? [open-ended]: Respondents could provide free-text answers.