Impact of Artificial Intelligence Adoption on Operational Efficiency in the Insurance Industry

Mr.Bommisetty Gnana Deep,Research Scholar ,BBA Department,KLEF,Vaddeswaram , gnanadeep18b@gmail.com ,.
Dr. Podile Venkateswara Rao,Professor,Head of Department,Department of BBA,KLEF, gnanadeepbommisetty3261@gmail.com
Guduri Nagaveni, Research Scholar, KL Business School, KLEF, Vaddeswaram, E-Mail: nagavenip.2207@gmail.com,

ABSTRACT

Artificial Intelligence has become a buzzword across industries, and insurance is no exception, with applications in customer service, claims processing, underwriting and fraud detection. However, many existing studies focus on individual applications. This study examines the relationship between AI adoption and perceived operational efficiency in the insurance industry, considering AI chat bots, claims automation, AI underwriting, fraud detection and AI-based customer service. Operational efficiency is measured through processing speed, accuracy and response time, among other dimensions. The research design was quantitative and cross-sectional, and data were gathered with a structured questionnaire on a five-point Likert scale. Convenience sampling was used to reach college students and insurance policyholders; 400 questionnaires were distributed and 78 completed responses were returned. Microsoft Excel was used for descriptive statistics, Cronbach's alpha, Pearson correlation, chi-square tests, one-way ANOVA and linear regression. The findings show a strong positive relationship between AI adoption and operational efficiency, with AI adoption accounting for 64.6% of the variance in operational efficiency; the null hypothesis was therefore rejected. Among the individual applications, fraud detection was the strongest predictor once it and AI-based customer service were added to the model, which increased explanatory power. Familiarity with AI and age were associated with perceptions of operational efficiency, whereas gender and prior insurance use were not. The main barriers to adoption were data privacy and security, lack of AI skills, and cost. Overall, the study provides empirical evidence from Indian respondents on the relationship between AI adoption and perceived operational efficiency. The results should be interpreted with caution given the small, non-probability sample, the predominance of young undergraduate respondents, and the use of perception-based measures from a single questionnaire.

Keywords: *Artificial Intelligence; AI adoption; operational efficiency; insurance industry; AI chat bots; claims automation; AI underwriting; India.*

1. INTRODUCTION

The insurance industry is undergoing major change with the increasing use of Artificial Intelligence and other digital technologies. Insurers previously relied primarily on manual processes, historical data, rules and human judgment for risk assessment, claims processing, customer service and fraud detection. With the abundance of data available today, insurers are turning to AI to perform many of these tasks more efficiently. Organizations can leverage AI for faster data processing, automation of repetitive tasks, better decision making, and improved overall operational performance.

AI is benefiting the insurance value chain at several stages. Eling et al. (2022) believe that AI can affect an insurer's risk assessment, underwriting, risk pricing, claims management and customer-facing operations, and could change the way insurers underwrite and manage risk. AI is therefore not a tool for one specific function but one that spans the value chain. Automation is another critical factor: Dong and Quan (2025) show that

automated machine learning makes it possible to process huge volumes of customer, policy, claims and risk data and to develop predictive models with less reliance on manual work. Bhattacharya et al. (2025) add that the benefits of AI for insurers' day-to-day operations deserve attention, as AI is gradually becoming a practical tool rather than an emerging technology in underwriting, claims, customer interactions, risk assessment and fraud detection.

AI is also making its mark in India. Mhaske and Shaikh (2025) examine its role in the Indian insurance industry, which has a large and diverse customer base and a wealth of customer, policy, claims and risk data. In this context, information technologies that can process data in time and support decision making are needed to improve business processes.

Insurers adopt AI in part because of the promise of improved operational efficiency. Operational efficiency is the effectiveness with which an organization uses its resources to carry out activities without compromising speed, accuracy and productivity. AI can support repetitive tasks, reduce processing time, increase accuracy, enable quicker data analysis, and help employees make better-informed decisions (Eling et al., 2022; Dong & Quan, 2025). However, adoption does not automatically increase an organization's efficiency. The benefits may vary with data quality, employee expertise, organizational readiness, technology systems, and the integration of AI with existing processes (Bhattacharya et al., 2025).

Although prior studies have addressed the use of AI, the automation of insurance processes and the effects on operational efficiency, empirical research on the relationship between AI adoption and operational efficiency is still needed. The present study, "Impact of Artificial Intelligence Adoption on Operational Efficiency in the Insurance Industry," therefore analyzes the relationship between operational efficiency parameters (processing time, accuracy, response time and others) and the application of AI in the insurance sector, namely AI chatbots, claims automation, AI underwriting, fraud detection and AI customer service.

2. REVIEW OF LITERATURE

Isa, Fernando and Fernando (2022) surveyed the use of AI in the insurance sector, exploring chatbots, big data, machine learning, block chain, fraud detection, claims processing, risk prediction and underwriting. They found that XGBoost and decision trees outperformed other techniques, while deep learning and explainable AI methods (LIME, SHAP) were not widely used.

Alkhelb and Alshagrawi (2025) explored the use of AI in health insurance underwriting. Using the PRISMA method to review 12 studies, they found that the most common use cases were fraud detection, underwriting, and claims processing via chatbots. They also identified data management and privacy issues and a lack of AI awareness as key challenges.

du Preez, Bhattacharya, Beling and Bowen (2025) examined machine learning for detecting health insurance fraud. They reviewed 137 studies, identified the most frequently used approaches over the previous twenty years, and found supervised learning to be the most effective method for detecting insurance fraud. They also noted that researchers often face poor data quality and a limited number of fraudulent claims for training these models.

Zafar and Wu (2026) reviewed 49 papers on explainable AI (XAI) in insurance fraud detection from 2021 to 2025. They found that most researchers attempt to resolve an "explainability/imbalance" paradox, namely that the method used to balance fraudulent and genuine claims affects the explainability of the results, and that several researchers fail to test the accuracy and reliability of their explainability methods.

Danda (2023) proposed achieving operational excellence in insurance through AI, suggesting that AI could be used to devise the most relevant offers for customers based on their data, behavior and preferences. Danda

argued that engaging customers in this way could boost wellness-program participation and encourage healthy living.

Owens et al. (2022) examined 419 studies on the use of XAI across the insurance value chain. The most common uses of explainable AI were in claims, fraud detection and pricing, and post hoc explainability methods, which explain the outcomes of black-box models, were the most widely used by insurers.

Eling, Nuessle and Staubli (2022) reviewed 91 academic and 22 industry studies to determine how AI is affecting the insurance value chain. They found that AI shifts insurance from a compensation mechanism to a mechanism for preventing losses before they occur, but that this transition also opens up new areas of uninsurability that the industry needs to address.

Singh and Chivukula (2020) studied machine learning and deep learning in insurance, focusing on underwriting automation and prospecting, and concluded that the use of AI in the industry is still at an early stage, with reinforcement learning, ensemble methods and natural language processing techniques likely to be applied in future.

Mhaske and Shaikh (2025) explored how AI is changing the Indian insurance sector. Using a descriptive research design, they examined the impact of AI on business efficiency, customer experience and innovation. Their results indicate that AI can improve process automation and provide more personalized services, although integration with existing systems and data security concerns hinder implementation.

Alam Khane et al. (2026) created an AI insurance agent using Retrieval-Augmented Generation, which supports more sophisticated responses to complex customer questions, suggests policies and helps with claims queries. Their findings indicate that it can be significantly better than conventional chatbots and human operators, who may be less accurate and consistent, and that AI can streamline operations, improve customer satisfaction and lead to cost savings.

Angadi (2025) pointed out that the effectiveness of AI in insurance should not be assessed on accuracy alone; speed, cost, scalability and the volume of data to be processed are equally critical. Case studies of five use cases, including claims processing and fraud detection, show how inefficient AI inference can undermine business outcomes.

Srinivas and Gandra (2023) surveyed 270 insurance agents in Andhra Pradesh on the relationship between AI adoption and sustainable practices, using a descriptive design and logistic regression. They found that the degree of AI adoption differs across companies, with some unable to afford such technologies, and that while automation and data integration are seen as areas where AI can be very useful, financial constraints and a lack of technical skills restrict its use.

Dong and Quan (2025) created an AutoML system that enables users with moderate technical skills to construct and train machine learning models. The system addresses the specifics of the data mining process, such as the selection and optimization of algorithms, and is particularly useful for the unevenly distributed labels typical of insurance data; the authors released it as open source.

Papastergiou, Basheer, Lampropoulos, Verrios and Islam (2026) combined explainable AI with large language models for cyber-insurance. Tested on an industrial 5G network, the solution identified the most vulnerable points in the network with high accuracy (96.9%), indicating that XAI can support the selection of specific cybersecurity measures and thereby improve the insurability of networks.

Paragioudakis et al. (2026) discussed data-driven technologies in cyber-insurance and highlighted emerging trends and gaps. They found that most insurers still rely on conventional questionnaires and take a reactive approach to cyber incidents, and that while insurers know how to use AI, data quality, standardization and explainability challenge adoption.

Bhattacharya, Castignani, Masello and Sheehan (2025) investigated how AI can be leveraged in auto, health and property insurance to identify the best opportunities for disruption. They found that the application of AI across these lines is not very different; for instance, AI can improve underwriting and risk exposure assessment, yet there is a danger of skewed data sets.

Pallathadka and Pallathadka (2021) studied the factors affecting AI adoption in the Indian insurance industry using a descriptive methodology and survey data, examining the strengths and weaknesses of AI in underwriting, claims processing, fraud detection and quote customization. Their findings indicate that AI can improve fraud detection and customer satisfaction, and that results were statistically significant for most of the AI applications studied.

Ahmad (2026) examined the combination of predictive analytics, IoT, cloud computing and agentic AI across the insurance value chain, taking the requirements of the EU AI Act into account. The author highlights four use cases: AI-powered telematics to track driver behavior; IoT processing of telematics data; cloud computing for real-time analytics; and agentic AI to facilitate operations across the value chain. Ensemble models such as Random Forest and XGBoost performed better than traditional logistic regression in claims classification, and the author believes telematics could reduce accidents and AI could help remove rating inequities.

Zarifis et al. (2019) investigated how insurers are transforming their business models with AI and identified four emerging models, including scenarios in which traditional insurers are replaced by disruptors and in which technology firms acquire traditional insurers. They concluded that activities in each part of the value chain will change due to AI, meaning that the industry will change gradually over time.

Omonova (2025) examined how AI can drive the digital evolution of the insurance sector, particularly in operational efficiency, risk management and personalization, and identified three areas where AI adds value, while noting that ethical concerns and uncertainties over data privacy and regulation remain.

3. RESEARCH GAP

While the literature has examined the impact of AI on specific insurance tasks such as underwriting, fraud detection, claims processing and customer service, little empirical evidence aggregates the impact of AI as an overall technology on operational efficiency. Most existing research is based on a single application, and the limited number of studies in India focus on risks, opportunities and sustainability, rarely on efficiency measures such as speed, accuracy and response time. This study aims to fill this gap using primary survey data.

4. PROBLEM STATEMENT

The insurance industry is adopting AI tools, including AI chatbots and claims automation, to streamline daily operations and improve customer service. Yet most studies examine applications one by one, and the impact of their implementation on overall operational efficiency, particularly in terms of processing speed, accuracy and response time, remains poorly understood. This study investigates the impact of these AI technologies on operational efficiency in the insurance sector.

5. RESEARCH QUESTIONS

RQ1. What is the relationship between AI adoption through AI chatbots, claims automation and AI underwriting and operational efficiency in the insurance industry?

RQ2. How does AI adoption through AI chatbots, claims automation and AI underwriting influence operational efficiency in terms of processing speed, accuracy and response time?

6. RESEARCH OBJECTIVES

- To identify the major applications of artificial intelligence in insurance operations.
- To analyze the impact of artificial intelligence adoption on operational efficiency in the insurance industry.
- To identify the major challenges associated with AI adoption in improving operational efficiency.

7. HYPOTHESES

Null Hypothesis ($H0^1$): Artificial Intelligence adoption has no impact on operational efficiency in the insurance industry.

Alternative Hypothesis ($H1^1$): Artificial Intelligence adoption has a positive impact on operational efficiency in the insurance industry.

Supplementary hypotheses, tested to profile how perceptions differ across respondent groups and technologies:

- **$H0_2$:** Perception that AI improves operational efficiency is independent of (a) AI familiarity, (b) age group, (c) insurance usage and (d) gender (chi-square).
- **$H1_2$:** Perception that AI improves operational efficiency is associated with (a) AI familiarity, (b) age group, (c) insurance usage and (d) gender (chi-square).
- **$H0_3$:** Mean operational efficiency scores do not differ across groups defined by (a) AI familiarity, (b) familiarity with AI in insurance, (c) age group and (d) insurance usage (one-way ANOVA).
- **$H1_3$:** Mean operational efficiency scores differ significantly across groups defined by (a) AI familiarity, (b) familiarity with AI in insurance, (c) age group and (d) insurance usage (one-way ANOVA).
- **$H0_4$:** AI chatbots, claims automation and AI underwriting have no individual significant effect on operational efficiency (multiple regression).
- **$H1_4$:** At least one of AI chatbots, claims automation and AI underwriting has a significant individual effect on operational efficiency (multiple regression).

8. RESEARCH METHODOLOGY

8.1 Research design and data collection

This study adopts a quantitative, cross-sectional survey design supported by secondary literature. A questionnaire (Google Forms) was used to gather primary data from college students and insurance policyholders on their awareness and perceptions of AI applications in insurance.

8.2 Sampling

Convenience sampling was employed. Four hundred questionnaires were sent out and 78 complete responses were used (19.5% usable response rate). The sample is therefore not necessarily representative of the population, and the results are not necessarily generalizable.

8.3 Instruments and measures

The questionnaire contains 26 items in four parts: (i) demographic and background items (age, gender, education, insurance use, familiarity with AI, and familiarity with AI in insurance; Q2–Q7); (ii) perceptions of AI applications (chatbots, claims automation, fraud detection, underwriting and customer service; Q8–Q12),

plus one multiple-choice item on the most important application (Q13); (iii) perceived operational efficiency (Q14–Q20); and (iv) challenges to adoption (Q21–Q26). Perceptual items were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Before the final analysis, the instrument was checked for validity and clarity.

Two composite indices were created as item means: the AI Adoption index (Q8–Q12; 5 items) and the Operational Efficiency (OE) index (Q14–Q19; 6 items). Overall efficiency (Q20) is reported separately and was used to classify respondents as "Agree" (score 4–5) or "Neutral/Disagree" (score 1–3) for the chi-square tests. For ANOVA and chi-square, familiarity categories were combined into Low (not at all/slightly), Moderate and High (very/extremely), and age categories into 20 or below, 21–23 years, and 24 or above, so that each group had sufficient respondents.

Table 1: Constructs, dimensions and questionnaire items

Construct	Dimension	Item (Q)	Code
AI adoption (independent)	AI chatbots	Q8	CB
	Claims automation	Q9	CA
	AI underwriting	Q11	UW
	AI fraud detection (additional)	Q10	FD
	AI customer service (additional)	Q12	CS
Operational efficiency (dependent)	Processing speed	Q14	PS
	Accuracy	Q15	AC
	Claims processing efficiency	Q16	CP
	Response time	Q17	RT
	Resource utilization	Q18	RU
	Service availability	Q19	AV
Overall perception	Overall operational efficiency	Q20	OV
Challenges	Cost, privacy, skills, integration, ethics/regulation, awareness	Q21–Q26	C1–C6

AI Adoption index = mean of CB, CA, UW, FD, CS. Operational Efficiency (OE) index = mean of PS, AC, CP, RT, RU, AV.

8.4 Statistical tools

All calculations were done in MS Excel using live formulas (COUNTIFS, AVERAGEIF, CHITEST, CHIINV, FDIST, FINV, TDIST, LINEST, CORREL). The tests used were descriptive statistics; Cronbach's alpha for reliability; Pearson correlation; chi-square tests of independence ($\alpha = 0.05$) with Cramér's V as the effect size; one-way ANOVA with eta squared and Bonferroni-adjusted pairwise t-tests as post hoc tests; and simple and multiple linear regression, with variance inflation factors (VIF) to check multicollinearity. Results were cross-checked with an independent calculation in Python and were consistent to the fourth decimal place.

9. DATA ANALYSIS AND RESULTS

9.1 Profile of respondents

Most respondents were male (87.2%), undergraduates (93.6%) and aged 18–23 years (76.9%). Just over half (52.6%) reported that they or their family had used an insurance product. AI familiarity was moderate (42.3% "moderately familiar"), but familiarity with AI in insurance was noticeably lower: 34.6% were not at all familiar and only 14.1% were very or extremely familiar.

Table 2: Demographic and background profile (n = 78)

Variable	Category	Frequency	Percent
Age	Below 18	3	3.8%
	18–20	35	44.9%
	21–23	25	32.1%
	24–26	7	9.0%
	Above 26	8	10.3%
Gender	Male	68	87.2%
	Female	10	12.8%
Education	Undergraduate	73	93.6%
	Postgraduate	5	6.4%
Insurance used by respondent/family	Yes	41	52.6%
	No	27	34.6%
	Not sure	10	12.8%
Familiarity with AI	Not at all	4	5.1%
	Slightly	21	26.9%
	Moderately	33	42.3%
	Very	12	15.4%
	Extremely	8	10.3%
Familiarity with AI in insurance	Not at all	27	34.6%
	Slightly	19	24.4%
	Moderately	21	26.9%
	Very	9	11.5%
	Extremely	2	2.6%
Most important AI application	AI chatbots	11	14.1%
	Claims automation	18	23.1%
	Fraud detection	26	33.3%
	AI underwriting	4	5.1%
	AI customer service	19	24.4%

Source: Primary data.

Fraud detection was chosen as the most important AI application by the largest share of respondents (33.3%), followed by AI customer service (24.4%), claims automation (23.1%), AI chatbots (14.1%) and AI underwriting (5.1%).

9.2 Descriptive statistics

Table 3 shows that respondents leaned towards agreement on every AI and efficiency item (means from 3.14 to 3.65). Among AI applications, fraud detection (M = 3.55) and AI customer service (M = 3.49) received the highest ratings and chatbots the lowest (M = 3.14). Among efficiency dimensions, reduced response time (M = 3.65) and faster processing (M = 3.55) were rated highest, and accuracy the lowest (M = 3.29). The overall means of the AI Adoption index (M = 3.37, SD = 0.62) and the OE index (M = 3.49, SD = 0.70) are both above the scale midpoint, and 53.8% of respondents agreed that AI can significantly improve operational efficiency (Q20).

Table 3: Descriptive statistics of AI adoption and operational efficiency items

Item	Mean	SD	% Agree (4–5)
CB – AI chatbots respond to queries efficiently	3.14	0.96	39.7%
CA – Claims automation improves claims efficiency	3.28	0.74	38.5%
UW – AI underwriting supports risk assessment	3.41	0.75	47.4%
FD – AI fraud detection identifies fraudulent claims	3.55	0.85	53.8%
CS – AI customer service improves quality/responsiveness	3.49	0.98	53.8%
PS – Processing speed	3.55	0.83	57.7%
AC – Accuracy	3.29	0.91	46.2%
CP – Claims processing efficiency	3.37	0.99	50.0%
RT – Response time	3.65	0.77	61.5%
RU – Resource utilization	3.51	0.88	59.0%
AV – Service availability	3.54	1.00	56.4%
OV – Overall operational efficiency	3.51	0.89	53.8%
ADOPT – AI Adoption index	3.37	0.62	17.9%
OE – Operational Efficiency index	3.49	0.70	32.1%

Scale: 1 = strongly disagree, 5 = strongly agree; n = 78. Source: Primary data.

9.3 Reliability

Cronbach's alpha was .765 for the five-item AI Adoption scale (acceptable), .869 for the six-item Operational Efficiency scale (good) and .888 for the six challenge items (good), so the composite indices are internally consistent enough for the tests that follow (Table 4).

Table 4: Reliability analysis

Scale	Items	Cronbach's α	Interpretation
AI Adoption	5	.765	Acceptable
Operational Efficiency	6	.869	Good
Challenges to adoption	6	.888	Good

Source: Primary data.

9.4 Correlation analysis

All correlations among the AI application items, the two indices and overall perception were positive (Table 5). The AI Adoption index correlated strongly with the OE index (r = .804), and each individual application also correlated positively with OE, most strongly claims automation (r = .627), chatbots (r = .608) and fraud detection (r = .594). Correlations among the predictors were moderate (r = .25 to .51), which suggests no serious multicollinearity.

Table 5: Pearson correlation matrix

Variable	1	2	3	4	5	6	7
1. Chatbots	1						
2. Claims automation	.437	1					
3. Underwriting	.334	.425	1				
4. Fraud detection	.365	.413	.254	1			
5. Customer service	.423	.510	.506	.346	1		
6. AI Adoption index	.731	.752	.677	.657	.787	1	
7. OE index	.608	.627	.527	.594	.552	.804	1

All coefficients are significant at $p < .05$ (n = 78). Source: Primary data.

9.5 Chi-square tests of independence

Chi-square tests examined whether the perception that AI improves operational efficiency (Q20: Agree vs Neutral/Disagree) depends on respondent characteristics (Table 6). Perception was significantly associated with AI familiarity and age group, but not with insurance usage or gender.

Table 6: Chi-square tests of independence with perception of AI-driven operational efficiency

Test	% Agree by group	χ^2	df	p	Cramér's V
AI familiarity	Low 36.0%; Moderate 51.5%; High 80.0%	8.78	2	.012	.336
Age group	≤20: 39.5%; 21–23: 68.0%; 24+: 66.7%	6.17	2	.046	.281
Insurance usage	Yes 63.4%; No 48.1%; Not sure 30.0%	4.15	2	.126	.231
Gender	Male 55.9%; Female 40.0%	0.88	1	.347	.107

N = 78 for each test. Smallest expected counts: 9.23 (familiarity), 6.92 (age), 4.62 (insurance usage and gender; one cell each below 5, so these two non-significant results should be read cautiously). Source: Primary data.

Respondents highly familiar with AI were far more likely to agree that AI improves operational efficiency (16 of 20, 80.0%) than those with low familiarity (9 of 25, 36.0%), a moderate-to-strong association (V = .336). Agreement was lowest in the youngest group (39.5% of those aged 20 or below) and about two-thirds among those aged 21 and above. Insurance usage showed the expected direction (63.4% of users agreed, against 30.0% of those unsure), but the difference was not statistically significant. $H0_2$ is therefore rejected for AI familiarity and age group, and not rejected for insurance usage and gender.

9.6 One-way ANOVA

One-way ANOVA compared mean OE index scores across groups (Table 7). Only familiarity with AI in insurance produced a significant difference ($F(2, 75) = 3.97$, $p = .023$, $\eta^2 = .096$, a medium effect). Bonferroni-adjusted comparisons showed that the highly familiar group ($M = 4.02$, $n = 11$) scored higher than both the low ($M = 3.42$, $n = 46$; $p = .032$) and moderate groups ($M = 3.36$, $n = 21$; $p = .032$), while the low and moderate groups did not differ ($p = 1.00$). General AI familiarity, age group and insurance usage showed no significant differences. Levene's tests indicated equal variances for all four analyses ($p = .196$ to $.844$), and a Kruskal–Wallis test supported the significant result ($p = .041$). $H0_3$ is rejected for familiarity with AI in insurance only.

Table 7: One-way ANOVA of the Operational Efficiency index by respondent groups

Grouping variable	Group means (n)	SS between	SS within	F(2, 75)	p	η^2
AI familiarity	Low 3.53 (25); Mod. 3.34 (33); High 3.67 (20)	1.379	36.552	1.415	.249	.036
Familiarity with AI in insurance	Low 3.42 (46); Mod. 3.36 (21); High 4.02 (11)	3.627	34.304	3.965	.023*	.096
Age group	≤20: 3.43 (38); 21–23: 3.57 (25); 24+: 3.48 (15)	0.294	37.638	0.292	.747	.008
Insurance usage	Yes 3.50 (41); No 3.51 (27); Not sure 3.35 (10)	0.217	37.715	0.216	.806	.006

** $p < .05$. SS total = 37.932 (df = 77) in every analysis. Source: Primary data.*

9.7 Regression analysis

Model 1 (simple regression). The OE index was regressed on the AI Adoption index (Table 8). The model was significant ($F(1, 76) = 138.86$, $p < .001$) and explained 64.6% of the variance in perceived operational efficiency (adjusted $R^2 = .642$; standard error of estimate = 0.420). A one-point rise in the AI Adoption index was associated with a 0.913-point rise in the OE index ($\beta = .804$, $t = 11.78$, $p < .001$). The intercept was not significant ($p = .131$). Residuals were approximately normal (Shapiro–Wilk $p = .166$) and showed no autocorrelation (Durbin–Watson = 2.07). $H0_1$ is rejected.

Table 8: Model 1 – simple linear regression (dependent variable: OE index)

Predictor	B	Std. error	β	t	p
Intercept	0.405	0.266	–	1.525	.131
AI Adoption index	0.913	0.078	.804	11.784	< .001

$R = .804$; $R^2 = .646$; adjusted $R^2 = .642$; $F(1, 76) = 138.855$, $p < .001$; $n = 78$. Source: Primary data.

Models 2 and 3 (multiple regression). Model 2 entered the three technologies named in the research questions (Table 9). It was significant ($F(3, 74) = 34.15$, $p < .001$), explained 58.1% of the variance (adjusted $R^2 = .564$), and all three predictors had positive, significant effects: claims automation ($B = 0.342$, $p < .001$), AI chatbots ($B = 0.267$, $p < .001$) and AI underwriting ($B = 0.237$, $p = .004$). In standardized terms, chatbots ($\beta = .367$) and claims automation ($\beta = .359$) contributed almost equally, with underwriting somewhat lower ($\beta = .252$). VIF values of 1.26–1.39 indicate no multicollinearity problem. $H0_4$ is rejected.

Model 3 added fraud detection and AI customer service, raising R^2 to .666 (adjusted $R^2 = .642$; $F(5, 72) = 28.65$, $p < .001$). Fraud detection became the strongest predictor ($\beta = .306$), followed by chatbots ($\beta = .280$), claims automation ($\beta = .239$) and underwriting ($\beta = .201$); AI customer service was not significant ($p = .241$), probably because it overlaps with claims automation and underwriting ($r = .51$ with each; VIF = 1.66).

Table 9: Models 2 and 3 – multiple linear regression (dependent variable: OE index)

Predictor	B	Std. error	β	t	p	VIF
Model 2 ($R^2 = .581$; adj. $R^2 = .564$; $F(3, 74) = 34.15$, $p < .001$)						
Intercept	0.717	0.292	–	2.459	.016	–
AI chatbots	0.267	0.062	.367	4.305	< .001	1.28
Claims automation	0.342	0.084	.359	4.055	< .001	1.39
AI underwriting	0.237	0.080	.252	2.977	.004	1.26
Model 3 ($R^2 = .666$; adj. $R^2 = .642$; $F(5, 72) = 28.65$, $p < .001$)						
Intercept	0.292	0.284	–	1.029	.307	–
AI chatbots	0.204	0.059	.280	3.495	.001	1.39
Claims automation	0.228	0.083	.239	2.760	.007	1.61
AI underwriting	0.190	0.077	.201	2.472	.016	1.43
Fraud detection	0.254	0.064	.306	3.956	< .001	1.29
AI customer service	0.075	0.063	.104	1.183	.241	1.66

Source: Primary data.

Efficiency dimensions (Research Question 2). Simple regressions of each efficiency dimension on the AI Adoption index (Table 10) were all positive and significant ($p < .001$). Adoption explained the most variance in perceived accuracy ($R^2 = .598$) and processing speed ($R^2 = .497$), and the least in response time ($R^2 = .193$), even though response time received the highest mean rating. This suggests that respondents agree that AI shortens response time regardless of how strongly they endorse AI across applications, whereas perceived gains in accuracy and speed rise more steeply with overall endorsement.

Table 10: Simple regressions of efficiency dimensions on the AI Adoption index

Dependent variable	B (slope)	r	R^2	t (df = 76)	p
Processing speed	0.949	.705	.497	8.667	< .001
Accuracy	1.143	.773	.598	10.629	< .001
Response time	0.548	.440	.193	4.269	< .001
Claims processing efficiency	0.869	.540	.291	5.589	< .001
Resource utilization	0.879	.618	.382	6.847	< .001
Service availability	1.091	.673	.452	7.924	< .001

Source: Primary data.

9.8 Challenges to AI adoption

Respondents endorsed all six barriers (means 3.41–3.85; Table 11). Data privacy and security concerns ranked first (M = 3.85; 65.4% agreed), followed by lack of employees with AI skills (M = 3.68; 60.3%). High implementation and maintenance costs and lack of awareness tied for third (M = 3.55 each), ethical and regulatory concerns ranked fifth (M = 3.50) and integration with existing systems sixth (M = 3.41).

Table 11: Challenges associated with AI adoption (ranked)

Rank	Challenge	Mean	SD	% Agree
1	Data privacy and security concerns	3.85	1.13	65.4%
2	Lack of employees with AI-related skills	3.68	0.96	60.3%
3 (tie)	High implementation and maintenance costs	3.55	1.03	50.0%
3 (tie)	Lack of awareness and understanding of AI	3.55	1.08	56.4%
5	Ethical and regulatory concerns	3.50	1.13	53.8%
6	Difficulty integrating AI with existing systems	3.41	1.00	46.2%

Source: Primary data.

9.9 Summary of hypothesis testing

Table 12: Summary of hypothesis testing

Hypothesis	Test	Result
$H0_1$: AI adoption has no impact on OE	Simple regression	$\beta = .804$, $R^2 = .646$, $p < .001$ (rejected)
$H0_2$(a): perception independent of AI familiarity	Chi-square	$\chi^2(2) = 8.78$, $p = .012$ (rejected)
$H0_2$(b): independent of age group	Chi-square	$\chi^2(2) = 6.17$, $p = .046$ (rejected)
$H0_2$(c): independent of insurance usage	Chi-square	$\chi^2(2) = 4.15$, $p = .126$ (not rejected)
$H0_2$(d): independent of gender	Chi-square	$\chi^2(1) = 0.88$, $p = .347$ (not rejected)
$H0_3$(a): OE equal across AI familiarity groups	ANOVA	$F(2, 75) = 1.42$, $p = .249$ (not rejected)
$H0_3$(b): OE equal across familiarity with AI in insurance	ANOVA	$F(2, 75) = 3.97$, $p = .023$ (rejected)
$H0_3$(c): OE equal across age groups	ANOVA	$F(2, 75) = 0.29$, $p = .747$ (not rejected)
$H0_3$(d): OE equal across insurance usage	ANOVA	$F(2, 75) = 0.22$, $p = .806$ (not rejected)
$H0_4$: chatbots, claims automation, underwriting have no effect	Multiple regression	All $p \leq .004$; $R^2 = .581$ (rejected)

Source: Primary data.

10. DISCUSSION

The key finding is a positive and statistically significant relationship between AI adoption and operational efficiency. The relationship between the AI Adoption index and the OE index is consistent with accounts of how AI improves efficiency by automating repetitive tasks, reducing processing time and facilitating decision making (Eling et al., 2022; Dong & Quan, 2025). It is also in line with Indian survey evidence showing statistically significant improvements from AI applications (Pallathadka & Pallathadka, 2021) and smoother processes (Mhaske & Shaikh, 2025).

The multiple-regression results indicate that the benefits do not come from a single technology. Chatbots, claims automation and underwriting were each standalone predictors, and fraud detection had the largest effect when added to the model. This aligns with the most frequent uses of AI, such as fraud detection, claims processing and customer assistance through chatbots (Alkhelb & Alshagrawi, 2025), and with the advantages of AI agents, including quicker and more consistent responses to customers (Alam Khane et al., 2026). Fraud

detection was also the application most often named as the most important (33.3%). Only 5.1% identified AI underwriting, and it had the smallest standardized effect among the key predictors, likely because underwriting is more internal and less visible to outside parties such as students or policyholders than the other applications.

Adoption was associated with higher perceived accuracy and processing speed. Response time had the highest average rating but was the weakest predictor in terms of variance explained by adoption. Angadi (2025) warns that while accuracy is important, so are latency, cost and scalability, and respondents' positive perception of speed and response time is consistent with the view that these operational metrics are vital to the business value of AI.

Knowledge mattered. More positive attitudes towards the efficiency impact of AI were found among respondents who were more familiar with AI, particularly with AI in insurance: 80% of the group with high AI familiarity agreed, compared with 36% of the low-familiarity group, and the group more familiar with AI in insurance had a significantly higher OE score. Lack of awareness was itself one of the barriers cited, with only 14.1% of respondents very or extremely knowledgeable about AI in insurance. This connects awareness with technology acceptance, a link identified earlier as a barrier to adoption (Alkhelb & Alshagrawi, 2025; Srinivas & Gandra, 2023). Prior use of insurance products did not significantly affect the results, indicating that perceptions of AI are driven by knowledge of AI in insurance rather than by insurance experience. The age result should be interpreted with caution because the youngest age group had the most respondents and the older groups were small.

Respondents identified data privacy and security as the most significant barrier, followed by lack of AI skills and cost. These are similar to barriers in the literature, such as privacy concerns and limited knowledge (Alkhelb & Alshagrawi, 2025), data security and ethical and regulatory uncertainty (Omonova, 2025), data protection and integration (Mhaske & Shaikh, 2025), and financial constraints and skills shortages among Andhra Pradesh insurance agents (Srinivas & Gandra, 2023). Integration with existing systems ranked last; it features heavily in the published literature, but respondents may be unfamiliar with legacy-system issues.

11. IMPLICATIONS

11.1 Managerial implications

- Insurers should view AI as a collection of complementary tools. Efficiency gains were strongest across chatbots, claims automation, fraud detection and underwriting, each of which had an independent link to efficiency.
- Data privacy and security, the biggest hurdle for stakeholders, should be addressed clearly through governance, consent and secure data handling.
- Insurers should invest in AI-skilled staff and in customer and employee awareness programmes, since awareness was linked to more positive perceptions and lack of skills was the second-ranked barrier.
- Cost and integration should be planned at the design phase, with new systems implemented in stages and with attention to how they integrate with existing systems (Bhattacharya et al., 2025).

11.2 Academic and policy implications

The study offers an empirical measurement model (the AI Adoption index and the Operational Efficiency index) that can be applied and validated in future research using insurer data. The findings reinforce the need for continued efforts in data protection, explainability and skills development, and for regulatory and industry initiatives such as the IRDAI Regulatory Sandbox (Bhuvaneshwari & Bheemanagouda, 2025).

12. LIMITATIONS AND SCOPE FOR FUTURE RESEARCH

- The sample was small (78 of 400 questionnaires distributed), non-probabilistic and unbalanced in composition, so the results may not apply to the entire insurance industry or the population of India.
- Respondents were primarily students and policyholders, not insurance employees or managers. The study therefore captures perceived operational efficiency, not actual operational efficiency.
- AI adoption and operational efficiency were assessed from the same respondents on the same questionnaire. This may have inflated the observed association and does not establish a cause-and-effect relationship.
- Some subgroups were very small, such as respondents very familiar with AI in insurance (11) and female respondents (10). Two chi-square tests had expected counts below 5, which may have limited statistical power.
- Future research should involve insurance employees, managers and industry experts to gain in-depth, practical experience of AI adoption and operational efficiency.
- Larger and more representative samples covering diverse population groups should be used.
- Actual company-level metrics such as claim processing times, claim settlement ratio, operating costs and error rates could be included.
- Future studies could compare AI adoption and operational efficiency between public and private insurers.
- Other factors such as organizational readiness, data quality, employee skills and technological infrastructure could also be explored.

13. CONCLUSION

This study analyzed the relationship between AI adoption and operational efficiency in the insurance sector using survey data from 78 respondents. Perceived operational efficiency was strongly and significantly related to AI adoption ($R^2 = .646$, $\beta = .804$). AI chatbots, claims automation and AI underwriting were each significant predictors of perceived efficiency, and fraud detection was also a strong predictor when added to the model. Respondents with greater knowledge of AI, especially of AI in insurance, perceived greater efficiency. Data privacy and security, lack of skills and cost were the main perceived barriers. The null hypothesis of no impact was rejected. Because the results rest on a small convenience sample and perceptual measures, they should be regarded as preliminary empirical evidence of a relationship between AI adoption and more efficient insurance operations, to be verified with larger samples and objective performance measures.

REFERENCES

1. Ahmad, J. (2026). The future of risk intelligence: Integrating predictive analytics across the insurance lifecycle. International Journal for Multidisciplinary Research, 8(2). https://www.ijfmr.com/papers/2026/2/75744.pdf

2. Alam Khane, S., Anarse, A., Shaikh, M., Chavan, N., & Korke, R. (2026). AI-based intelligent insurance agent using retrieval-augmented generation. International Journal of Electrical, Electronics and Computer Systems, 15(1s), 71–76. https://doi.org/10.65521/ijeecs.v15i1S.2957

3. Alkhelb, A. A., & Alshagrawi, S. (2025). Role of artificial intelligence in healthcare insurance: Systematic literature review. Exploration of Digital Health Technologies, 3, Article 101145. https://doi.org/10.37349/edht.2025.101145

4. Angadi, A. (2025). AI inferencing optimization in insurance: Evaluating the impact of latency, cost, throughput, and scalability on AI-driven business outcomes across the insurance value chain. International Journal for Multidisciplinary Research, 7(6). https://www.ijfmr.com/papers/2026/2/78059.pdf.

5. Bhattacharya, S., Castignani, G., Masello, L., & Sheehan, B. (2025). AI revolution in insurance: Bridging research and reality. Frontiers in Artificial Intelligence, 8, Article 1568266. https://doi.org/10.3389/frai.2025.1568266.

6. Danda, R. R. (2023). AI-driven incentives in insurance plans: Transforming member health behavior through personalized preventive care. Letters in High Energy Physics, 2023(196). https://lettersinhighenergyphysics.com/index.php/LHEP/article/download/819/495/

7. Dong, P., & Quan, Z. (2025). Automated machine learning in insurance. Insurance: Mathematics and Economics, 120, 17–41. https://doi.org/10.1016/j.insmatheco.2024.10.008

8. du Preez, A., Bhattacharya, S., Beling, P., & Bowen, E. (2025). Fraud detection in healthcare claims using machine learning: A systematic review. Artificial Intelligence in Medicine, 160, Article 103049. https://www.sciencedirect.com/science/article/pii/S0933365724003038

9. Eling, M., Nuessle, D., & Staubli, J. (2022). The impact of artificial intelligence along the insurance value chain and on the insurability of risks. The Geneva Papers on Risk and Insurance – Issues and Practice, 47, 205–241. https://doi.org/10.1057/s41288-020-00201-7

10. Isa, U. A., Fernando, A., & Fernando, T. G. I. (2022). Artificial intelligence for insurance industry: A survey (Preprint). Research Square. https://doi.org/10.21203/rs.3.rs-1766398/v1

11. Mhaske, A., & Shaikh, N. (2025). Exploring the role of artificial intelligence in India's insurance sector. Allana Management Journal of Research, 15(2), 13–19. https://www.researchgate.net/publication/394307533

12. Omonova, D. D. (2025). The impact of artificial intelligence technologies on the processes of digital transformation in the insurance industry. Yashil Iqtisodiyot va Taraqqiyot (Green Economy and Development), 3(11), 11–19. https://zenodo.org/records/17630416

13. Owens, E., Sheehan, B., Mullins, M., Cunneen, M., Ressel, J., & Castignani, G. (2022). Explainable artificial intelligence (XAI) in insurance. Risks, 10(12), Article 230. https://doi.org/10.3390/risks10120230

14. Pallathadka, H., & Pallathadka, L. K. (2021). An empirical study on risk and opportunities of use of artificial intelligence in the Indian insurance sector. International Journal of Psychosocial Rehabilitation, 25(3). https://www.psychosocial.com/index.php/ijpr/article/download/1236/1113/2227

15. Papastergiou, S., Basheer, N., Lampropoulos, K., Verrios, P., & Islam, S. (2026). Explainable AI based dynamic cybersecurity risk management for cyber insurability. International Journal of Information Security, 25, Article 36. https://doi.org/10.1007/s10207-025-01189-8

16. Paragioudakis, A., Komninos, N., Smyrlis, M., Spanoudakis, G., & Kloukinas, C. (2026). Risk management for cyber insurance: A survey for data-driven approaches with the use of AI. International Journal of Information Security, 25, Article 112. https://doi.org/10.1007/s10207-026-01275-5

17. Singh, S. K., & Chivukula, M. (2020). A commentary on the application of artificial intelligence in the insurance industry. Trends in Artificial Intelligence, 4(1), 75–79. https://scholars.direct/Articles/artificial-intelligence/tai-4-008.pdf

18. Srinivas, B., & Gandra, P. K. (2023). Role of artificial intelligence in Indian insurance industry: Challenges and opportunities from sustainability perspectives. Journal of Informatics Education and Research, 3(2). https://doi.org/10.52783/jier.v3i2.468

19. Zafar, U., & Wu, F. (2026). Methodological challenges in explainable AI for fraud detection: A systematic literature review. Artificial Intelligence Review. https://www.researchgate.net/publication/400876946

20. Zarifis, A., Holland, C. P., & Milne, A. (2019). Evaluating the impact of AI on insurance: The four emerging AI- and data-driven business models. Emerald Open Research, 1, Article 15. https://doi.org/10.35241/emeraldopenres.13249.1