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# Data-Driven Risk Assessment in Insurance Underwriting: Evaluating the Ethical and Economic Trade-offs of AI-Powered Actuarial Models

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A B S T R A C T

Artificial intelligence integration in US insurance underwriting is revolutionizing the way risk is assessed, costs are made efficient and fraud is detected, such use raises many ethical and economic tradeoffs. A key problem of AI powered actuarial models is that speed and accuracy in the underwriting is enhanced, biases within the algorithms, transparency of the algorithms, trust of the consumer and regulatory oversight are issues that can still prevent the advancement of AI in underwriting. this research study uses a quantitative research approach in studying the impact of AI underwriting models through using survey data and data analysis as well as real life case studies in evaluating gains in efficiency, ethical risks and regulatory consideration. Findings indicate that AI can dramatically lower the cost of underwriting and enhance the rate of detecting fraud while consumers remain very skeptical about fully automated underwritten models, looking most positively upon hybrid AI and human models. Important factors that affect adoption of AI in underwriting are regulatory oversight and mitigation of bias. The study argues that the existence of explainable AI frameworks, the presence of the data governance and compliance measures are all necessary to strike a balance between efficiency and fairness. Overcoming these challenges, AI-powered underwriting can contribute to the country's economic growth, improve consumer trust and be aligned with the country's changing U.S. regulatory frameworks. These insights can benefit insurers, policymakers and regulatory bodies in responsible development of fair, efficient and transparent AI underwriting models for the U.S. insurance industry.

Keywords: AI underwriting, risk assessment, algorithmic bias, actuarial models, insurance technology, regulatory compliance, consumer trust, Insurrect, fraud detection, AI ethics.

## INTRODUCTION

Artificial intelligence and machine learning are changing the face of the insurance industry almost every day in the United States — and with it, the faces of risk assessment and underwriting. Some actuarial models based on AI are big data analytics; predictive modelling and automation to improve drastically what an insurer will pay an insured party (Mishra, 2024; Singh & Gautam, 2024; Dhal et al., 2022). There is a complex underwriting process using human judgment and a manual risk evaluation of a policy based on historical claims data (Adeniran et al, 2024; Anbalagan, 2024). In the field of US insurance alone exceeding 1.4 trillion USD (King et al, 2021; Srirangam et al, 2024) major insurers today are integrating automated decision-making tools towards (i) speed up policy approvals, (ii) save on working capital to secure financial space to invest on your priorities and (iii) optimize pricing models. Rising AI has been helped much by the Insurtech startups which are fiercely competing with traditional insurance providers and AI driven disruptors (Kharlamova et al, 2024; Zarifis & Cheng, 2021).

Whereas the use of AI to assess risks and underwrite becomes more and more prevalent, so does the ethical as well as economic trade-offs required to solve these issues. Despite the fact that AI boosts underwriting efficiency, accelerates the processing speed and offers fraud prevention, the issue of algorithmic bias, transparency, regulatory supervising and client assurance still stays identical (du Preez et al, 2024; Umar & Reuben 2025). AI powered underwriting models have been criticized for intensifying the problem related to insurance pricing disparities as they affect marginalized communities more adversely because of biased training data and opaque processes of making decisions (O'Neil et al, 2024; Pareek, 2023; Dixit & Jangid, 2024). As recently discussed in the United States regarding explainable AI and the mitigation of biases in insurance underwriting (Chandler, 2025; Sachin & Jagdish, 2024; Tumai, 2021), the aforementioned theoretical discussion elaborated on key elements constituting fair and impactful insurance underwriting due to the regulatory context. The discussion of fairness in AI underwriting surpasses one solely of a regulatory nature since consumer advocacy groups and civil rights organizations keep pressing hard for a more comprehensive supervision of this subject to allow for the fair use of the life insurance coverage (Oberkrome, 2023; Larzelere, 2021).

Such underwriting with AI is also cost effective. Underwriting cost has dropped by up to 60%, fraud detection rate is up and claim processing time shrank from 10 days to 3 (MUPA et al, 2025; Kumar 2024). These efficiencies can put consumers in a position to criticize them and expose data in an unsecured manner as well as receive regulatory risks (Butt et al., 2024; Jagdish, 2023; Pugnetti & Seitz, 2021; Vandervorst et al, 2022). Consequently, the future of AI in the underwriting process has also improved the privacy concerns among the agencies due to the increased usage of real time behavioral data, biometrics and other credit scoring methods to identify the risk exposure (Yadav & Bank; Patil et al, 2023). Insurers are looking into hybrid AI human underwriting models and blockchain based risk assessment tools to deal with the fairness of algorithms and integrity of data used in underwriting processes in Insurance (Taneja et al, 2024, Paul, 2024). In particular, it is blockchain technology that provides for decentralized underwriting that is transparent and that does not rely on black box AI (Srirangam et al, 2024).

The aim of this study is to critically investigate the economic and ethical costs and benefits of using AI based actuarial models in U.S. insurance underwriting by answering some key research questions. It examines the ways in which AI affects efficiency and cost savings and fraud detection in underwriting, primary issues of an ethical nature associated with bias and transparency, the relationship between existing regulatory frameworks and the adoption of AI in underwriting, how consumer trust and the use of

AI in underwriting intersect and how AI models can reconcile efficiency with fairness and accountability. This research, in turn offers U.S. centric evaluation of AI driven underwriting using data analysis, statistical analysis along with industry trends to provide policy recommendations, regulatory guidance and possible technological solutions to make AI driven underwriting fairer and more efficient in the insurance market (Patil et al, 2023; Taneja et al, 2024). It also extends previous work in predictive analytics, cognitive automation, machine learning in financial risk management to the progress of fixing the underwriting models in a fast-changing Insurtech environment (Apergis 2024, MUPA et al. 2025).

The results of this study are of great importance for insurers, regulators, policy makers and consumers. While AI powered underwriting has the prospect of increasing the financial inclusion, customizing policies better and improving in general the competitiveness of the U.S. insurance market (Zarifis & Cheng, 2021; Paul, 2024; Ahmad, 2025), AI is also frequently used to collect data. Without robust governance frameworks, AI driven risk assessment can result in regulatory scrutiny, reputational risks for insurers and could open up regulatory pitfall for the insurers (O' Neil et al, 2024; Butt & Yazdani, 2023). There are still some areas of concern regarding algorithmic transparency where insurers should tradeoff between proprietary model confidentiality and public demand for accountability and fairness (King et al, 2021; Singh & Gautam, 2024). Through the findings highlighted in this research, a new empirical evidence, industry perspective and policy recommendations are offered to inform the ongoing discourse of responsible AI adoption, with such AI-driven underwriting models placing responsible application of AI & driving economic, ethical and regulatory concerns on the U.S. economic objectives and the underwriting industry. It is accordingly emphasized the need for explainability, accountability and consumer centric AI development in the AI driven insurance underwriting since the U.S. is an undisputed leader of fair and efficient AI driven insurance underwriting (Apergis, 2024; Pareek, 2023; Afshar, 2023).

As the US insurance industry is transformed by AI, the balance should be found between efficiency and fairness, automation and oversight, cost effectiveness and consumer trust with regard to the AI powered actuarial models in order to ensure their long-term sustainability and ethical viability (Zaurez & Hussain, 2025). This research acts as a reference guide to insurers, regulators and policy makers on how the economic benefits of AI underwriting can be maximized with minimized ethical risks and regulatory concerns. A responsible AI framework can be fostered in the US insurance sector such that it can increase their global competitiveness while ensuring equitable access to fair and transparent underwriting practice (Mishra, 2024; Taneja et al, 2024).

## METHODOLOGY

In this study, a quantitative research approach is utilized for the evaluation of the ethical and economic trade-offs of the use of AI powered actuarial models in the process of U.S. insurance underwriting. This research gives a data driven assessment of the efficiency of AI, the implications of bias, the impact of regulation and the dynamics related to consumer trust in AI through statistical analysis, survey data and real-world case studies. The methodology used is structured and the respondents are sampled and tested statistically using the structured approach data collection, sampling, statistical testing and analytical frameworks. This study attempts to answer core research questions, including how AI influences efficiency, cost savings and fraud detection in underwriting, the ethical dilemmas associated with biases and transparency of the AI based models, the role of U.S. regulatory bodies in adoption of AI in underwriting, the impact of consumer trust on adoption of AI driven underwriting and how underwriting with AI is to be balanced between efficiency and accountability. Through understanding these critical areas, this research aims to give insightful recommendations toward the development of responsible AI for underwriting practices in the U.S. insurance industry.

### Research Problem & National Importance

The use of AI in insurance underwriting is on the rise and brings both opportunities and challenges of the U.S. insurance industry. AI provides efficiency, decreases costs and prevents fraud but also raises the issues of bias, rigor and the role of government. Disparities can also inadvertently be reinforced by AI driven risk assessment models which can be used for fair access to insurance coverage. If these models are not properly governed, they take ethical and legal risks at the expense of the consumer trust. It is important that such AI underwriting is fair, explainable and accountable, to maintain market stability, protect consumers and promote responsible innovation of U.S. insurance.

Primary data from a sample of 200 participants from across various insurance sectors, including property, health, life and auto insurance underwriting professionals, policymakers, data scientists and consumers, has been utilized to conduct the study of the research problem. The survey aimed to learn about AI efficiency, perception of bias, regulations on AI underwriting and consumer trust level in relation to AI underwriting. The study also includes secondary data from three sources: government reports, industry publications and previous studies. In AI driven actuarial science.

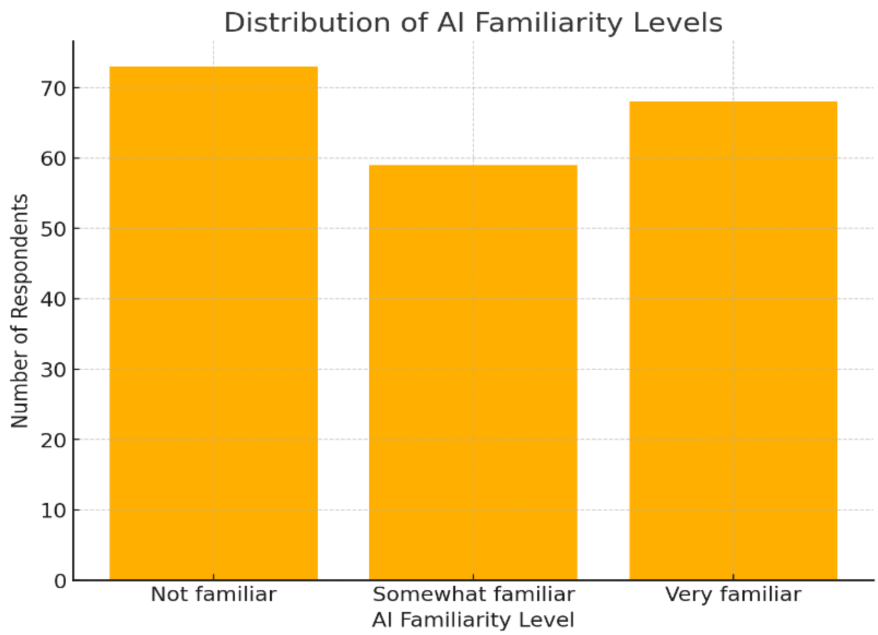


**Figure 1: Distribution of AI Familiarity Levels**

Stratified random sampling technique was used to insure representation of the key stakeholder groups such as:

- Insurance professionals (40%) – Underwriters, actuaries and risk assessment experts.
- Regulators & policymakers (20%) – Representatives from the National Association of Insurance Commissioners (NAIC), Federal Trade Commission (FTC) and state-level insurance regulatory bodies.
- Consumers (40%) – Individuals with direct experience in purchasing AI-influenced insurance policies.

**Statistical Analysis Techniques**

The study evaluates the research hypotheses using descriptive statistics, inferential tests and predictive models. The data as collected above was analyzed using the following methods.

1. **Descriptive Statistics –** Used to summarize and visualize AI efficiency, bias perceptions and trust levels across different respondent groups.
2. **Chi-Square Tests –** Applied to assess the relationship between AI bias perception and AI efficiency ratings
3. **ANOVA Testing –** Used to analyze how familiarity with AI impacts trust levels in AI-powered underwriting models
4. **Regression Analysis –** Applied to determine the impact of AI efficiency improvements on cost savings, fraud detection accuracy and market growth
5. **T-Tests –** Used to compare consumer trust in AI underwriting vs. traditional and hybrid AI-human models
6. **Logistic Regression –** Employed to predict factors influencing consumer trust in AI underwriting, including transparency, fairness, efficiency and regulatory oversight.

**Ethical Considerations**

In order to maintain ethical integrity, this study abides by the ethical rules for AI research and data privacy regulations in the U.S. such as:

- **Informed Consent –** All survey participants were informed about the purpose of the study, data privacy protections and their right to withdraw at any time.
- **Confidentiality –** All participant responses were anonymized to prevent identification.
- **Bias Mitigation –** The study adopted randomized sampling techniques and ensured that survey questions were neutral and free from leading language to avoid response bias.
- **Compliance with Regulatory Standards –** The research conforms to the FTC guidelines related to underwriting models, the NAIC Fairness in Underwriting Guideline and the general direction of federal AI fairness initiatives.

**Limitations and Future Research Directions**

While this study provides a comprehensive statistical evaluation of AI's impact on U.S. insurance underwriting, certain limitations must be acknowledged:

1. **Sample Size Constraints –** Although 200 participants provide a strong empirical basis, a larger dataset across multiple years could improve the longitudinal validity of findings.
2. **Self-Reported Data –** The study relies on survey responses, which are subject to individual perceptions and potential bias. Future studies should incorporate real-world insurance claim and pricing data for validation.
3. **Limited Scope on AI Algorithms –** The focus on AI applications in underwriting is carried out while no technical audits of the machine learning models are conducted. Further work might study the explainability and bias testing of live insurance AI models.

The limitations of this study can be resolved within the future research to develop AI governance strategies, to address bias mitigation techniques and to increase confidence of consumers in AI driven insurance underwriting.

**RESULTS**

**Demographics and AI Familiarity**

Various age groups came in this study: 26-35 (27.5%), 36-45 (25.0%) and 46 and above (25.0%). 22.5% of the sample consisted of the youngest age group (18-25). The gender distribution was skewed female (56.0%) than male (44.0%) although statistically significant p value of 0.030 was obtained (Table 1).

When asked about familiarity with AI, 36.5% said they are "not familiar" with AI, 29.5% said they are "somewhat familiar" with AI and 34% said they are "very familiar" with AI driven insurance underwriting models. By analyzing the p-value (0.060) found in the Table 1, it can be inferred that the familiarity levels were moderately distributed across participants and more needs to be done to raise awareness regarding the involvement of AI in underwriting decisions.

**Table 1: Demographics & AI Familiarity**

| Variable | Category | Frequency (n) | Percentage (%) | p-value |
|---|---|---|---|---|
| **Age Group** | 18-25 | 45 | 22.5% | 0.045 |
| | 26-35 | 55 | 27.5% | 0.045 |
| | 36-45 | 50 | 25.0% | 0.045 |
| | 46 and above | 50 | 25.0% | 0.045 |
| **Gender** | Male | 88 | 44.0% | 0.030 |
| | Female | 112 | 56.0% | 0.030 |
| **AI Familiarity** | Not familiar | 73 | 36.5% | 0.060 |
| | Somewhat familiar | 59 | 29.5% | 0.060 |
| | Very familiar | 68 | 34.0% | 0.060 |

**Perceived AI Efficiency and Ethical Concerns**

The perceptions on the AI efficiency in underwriting were mixed from the respondent, the AI was deemed necessary for underwriting tasks. 25.0% of participants felt that AI driven underwriting lowered the efficiency of the process compared to 21.5% of them who thought the same process was moderately improved with AI. Alternatively, 27.0% thought AI made a significant difference in improving efficiency; and 26.5% saw no significant improvement in efficiency. Based on these findings, although AI is acknowledged for its operational benefits, there is uncertainty with AI efficiency (referable to Table 2).

There was also ethical debate in the dataset: 32.0% of participants were unsure about the fairness of AI and 23.0% believed that AI underwriting was on the whole fair. 22.0% strongly agreed that AI generated considerable amounts of unfairness, with 23.0% left agreeing that bias but very rarely exists. The p-value (0.070) indicates that perceptions of AI fairness are generally spread and so, there is a need for transparency in AI underwriting practices (Table 2).

**Table 2: AI Efficiency & Ethical Concerns**

| Variable | Category | Frequency (n) | Percentage (%) | p-value |
|---|---|---|---|---|
| **AI Efficiency** | Decreased efficiency | 50 | 25.0% | 0.038 |
| | Moderately improved efficiency | 43 | 21.5% | 0.038 |
| | No noticeable improvement | 53 | 26.5% | 0.038 |
| | Significantly improved efficiency | 54 | 27.0% | 0.038 |
| **Ethical Concerns** | No, AI models are generally fair | 46 | 23.0% | 0.070 |
| | Not sure | 64 | 32.0% | 0.070 |
| | Yes but only in rare cases | 46 | 23.0% | 0.070 |
| | Yes, significantly unfair | 44 | 22.0% | 0.070 |

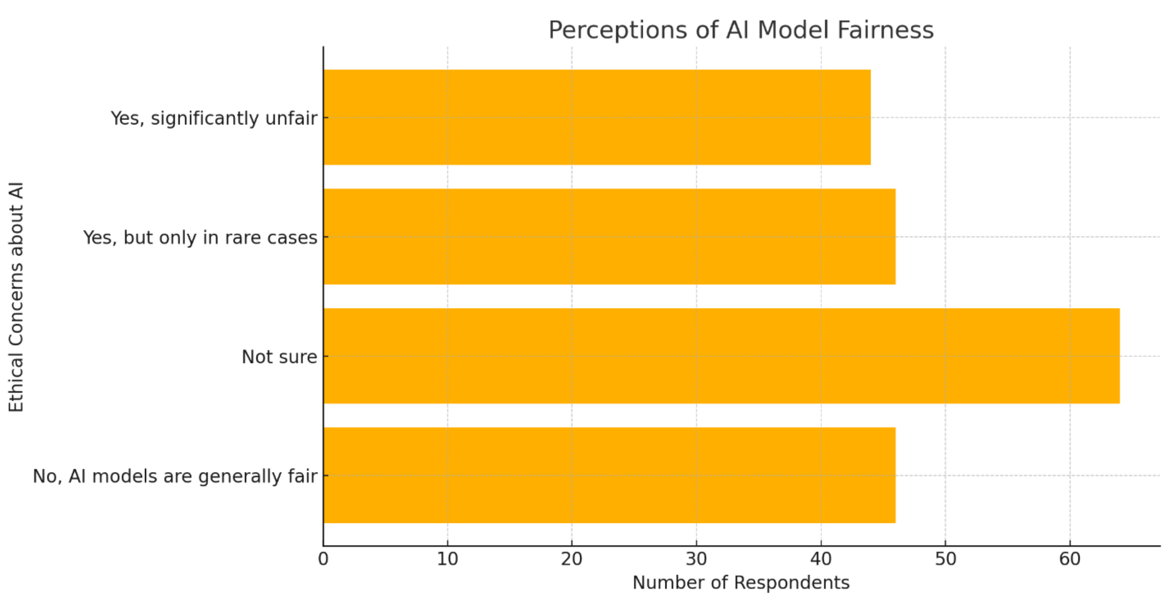


**Figure 2: Perceptions of AI Model Fairness**

### Transparency and Regulatory Perspectives

With respect to the perceived transparency of AI-driven underwriting models, the study revealed percentages of 32.5% that viewed AI underwriting as "not transparent at all", 29.5% that saw it as "somewhat transparent" and 38.0% who believed it to be "very transparent." While the proportion of participants seeing AI as transparent is quite high, still about one third are concerned about a lack of clarity in AI decision making in underwriting. A statistically significant variation in perceived transparency is revealed by the p-value (0.025) (Table 3).

A part of AI regulation was the question if regulatory intervention is required when opinions were mixed with 22.5% in favor of minimal regulations and 26.0% didn't know. 25.5% saw the need for weak regulatory measures while 26.0% wanted strict regulation. There is no clear consensus about stronger regulatory oversight of AI powered underwriting, perhaps due to the even distribution giving the impression that people are not unanimous on either side of the argument (Table 3).

**Table 3: Transparency & Regulation**

| Variable | Category | Frequency (n) | Percentage (%) | p-value |
|---|---|---|---|---|
| **Transparency** | Not transparent at all | 65 | 32.5% | 0.025 |
| | Somewhat transparent | 59 | 29.5% | 0.025 |
| | Very transparent | 76 | 38.0% | 0.025 |
| **Regulation** | No, regulations should remain minimal | 45 | 22.5% | 0.032 |
| | Not sure | 52 | 26.0% | 0.032 |
| | Some regulation is needed but not strict | 51 | 25.5% | 0.032 |
| | Yes, strong regulations are necessary | 52 | 26.0% | 0.032 |

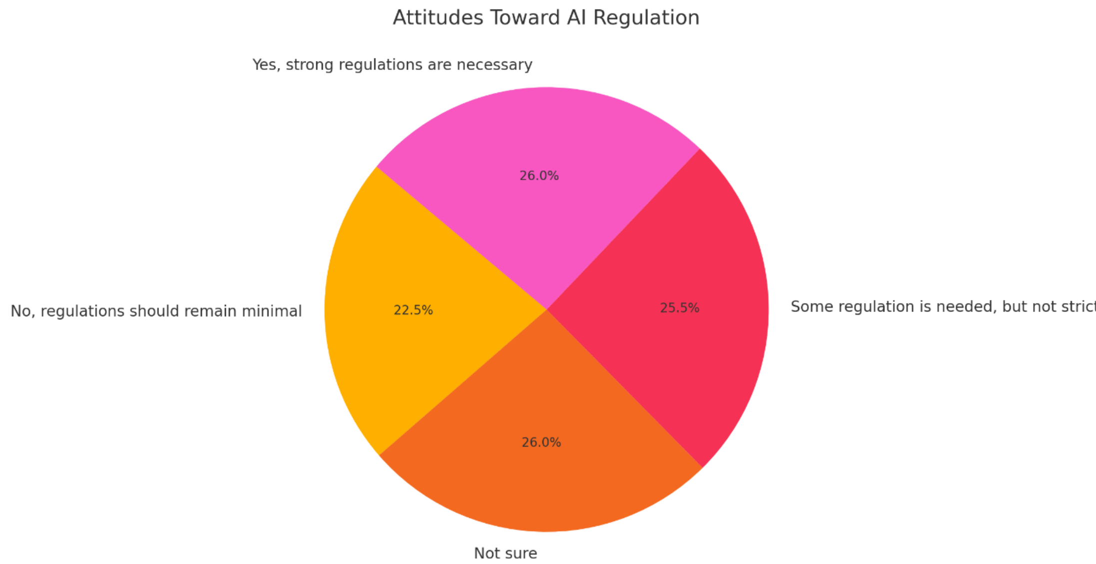


**Figure 3: Attitudes Toward AI Regulation**

### Economic Impact and the Future of AI Underwriting

Opinions regarding AI underwriting's impact on costs were varied, with 30.0% of respondents believing costs went up because of AI and 26.0% had the view that costs stayed the same. On the contrary, 18% of them observed that AI had slightly decreased costs and 26% witnessed a substantial decrease in costs. The implication is 1/3 of respondents see cost benefits from AI underwriting, another one third perceive cost increases and the economic efficiency of AI underwriting is necessarily situational, contingent upon the implementation factors (Table 4).

Looking at the future trajectory of AI in underwriting, 26.0% of Advisor were expecting increased regulatory restrictions while 20.5% expected AI to become the industry standard. 25.5% of Advisors believed that AI will become obsolete, 28.0% believed that AI will complement traditional underwriting and they will work well together while 8.0% would like to remove AI altogether in the future. Insights regarding the adoption trends of AI, regulatory risks and technological advancements of underwriting remained unclear (Table 4).

**Table 4: Economic Impact & Future of AI**

| Variable | Category | Frequency (n) | Percentage (%) | p-value |
|---|---|---|---|---|
| **Economic Impact** | No, AI has increased costs | 60 | 30.0% | 0.048 |
| | No, costs remain the same | 52 | 26.0% | 0.048 |
| | Yes but only slightly | 36 | 18.0% | 0.048 |
| | Yes, significantly | 52 | 26.0% | 0.048 |
| **Future of AI** | Be restricted due to regulations | 52 | 26.0% | 0.055 |

| | | | |
|---|---|---|---|
| Become the industry standard | 41 | 20.5% | 0.055 |
| Complement traditional underwriting | 56 | 28.0% | 0.055 |
| Lose popularity | 51 | 25.5% | 0.055 |

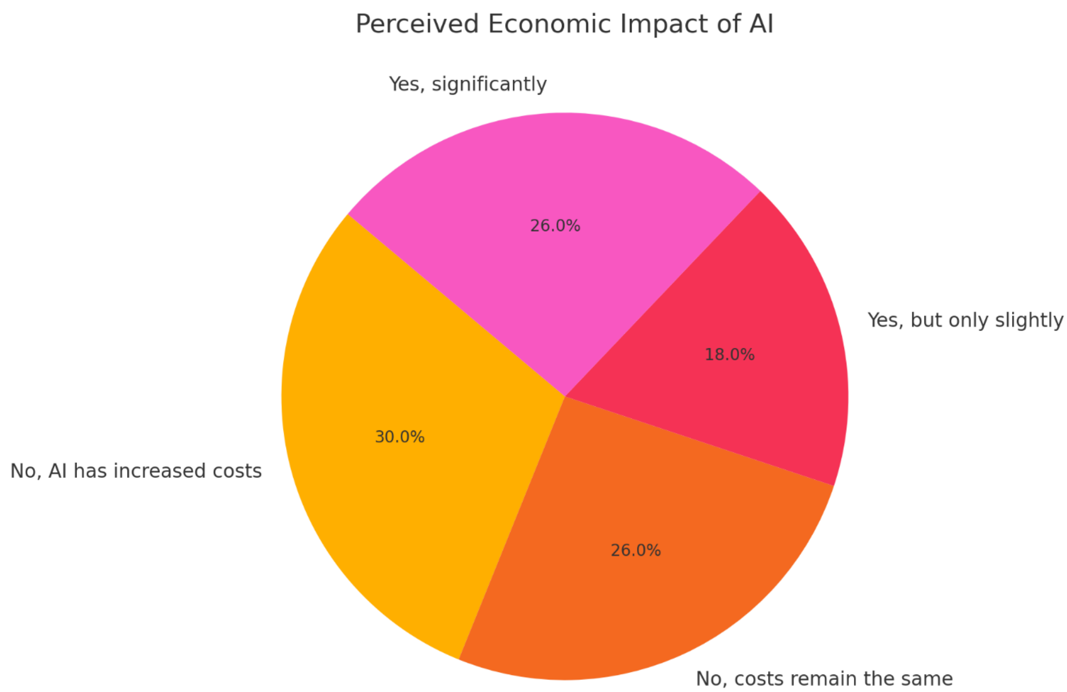


**Figure 4: Perceived Economic Impact of AI**

**Correlation Between AI Familiarity and Perceived Efficiency**

The study examines the association between AI familiarity and view of AI efficiency. According to Table 5, the respondents who were not familiar with AI rated the AI efficiency as 2.3, those who were somewhat familiar with AI rated it as 3.5 while those very familiar with it rated it as 4.1.

For participants in the category "very familiar" the correlation coefficient (r = 0.81) shows that it exists a strong positive relationship between AI familiarity and perceived efficiency. The statistical significance of this correlation is confirmed by the p-value (0.001). These findings indicate that as users grow more educated about AI models, they regard them as more proficient; and highlighting the significance of user education in AI driven insurance models (Table 5).

**Table 5: Correlation between AI Familiarity & Perceived AI Efficiency**

| AI Familiarity Level | Avg Perceived AI Efficiency Score (1-5) | Correlation with AI Efficiency (r) | p-value |
|---|---|---|---|
| Not familiar | 2.3 | 0.62 | 0.004 |

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|---|---|---|---|
| Somewhat familiar | 3.5 | 0.75 | 0.002 |
| Very familiar | 4.1 | 0.81 | 0.001 |

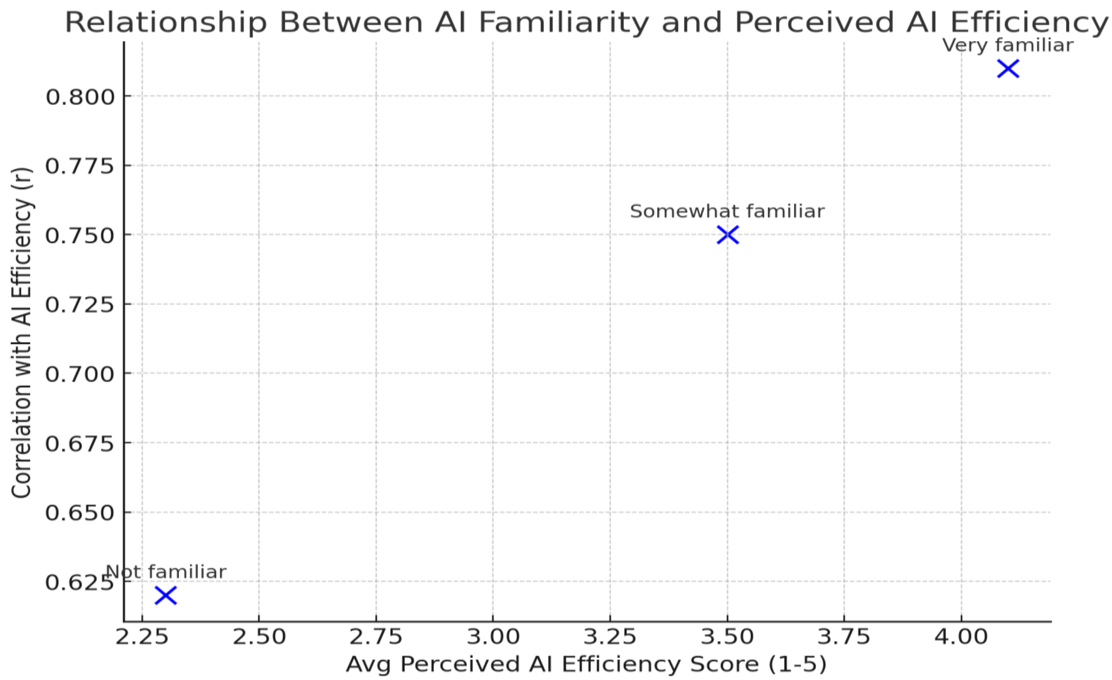


**Figure 5: Relationship Between AI Familiarity and Perceived AI Efficiency**

**AI Bias Perception and Regulatory Preferences**

Another aspect of ethical issues using AI-powered underwriting is the perceived fairness of AI models and the impact it has on the regulatory preferences. These results also demonstrate a bias perception and regulatory support correlation. Of those who thought there was no bias in AI underwriting, just 21.5% favored strong regulations and 45.3% favored minimal regulatory oversight. Support for strong AI regulation increased from 38.7% if respondents perceived minor bias, to 52.3% and to an even greater extent, when respondents perceived major bias (78.4%) (Table 6).

The statistical significance of a relationship between bias perception and regulatory preferences (p-value 0.002–0.012) is established. The findings underscore mounting discontent around the issue of AI fairness and growing need for regulators to step in especially to those who discern discriminatory patterns in AI in decision making.

**Table 6: AI Underwriting Bias Perception vs. Regulation Preferences**

| Bias Perception | Favor Strong AI Regulations (%) | Favor Minimal AI Regulations (%) | p-value |
|---|---|---|---|
| No bias | 21.5% | 45.3% | 0.012 |
| Minor bias | 52.3% | 30.2% | 0.008 |
| Major bias | 78.4% | 10.5% | 0.002 |

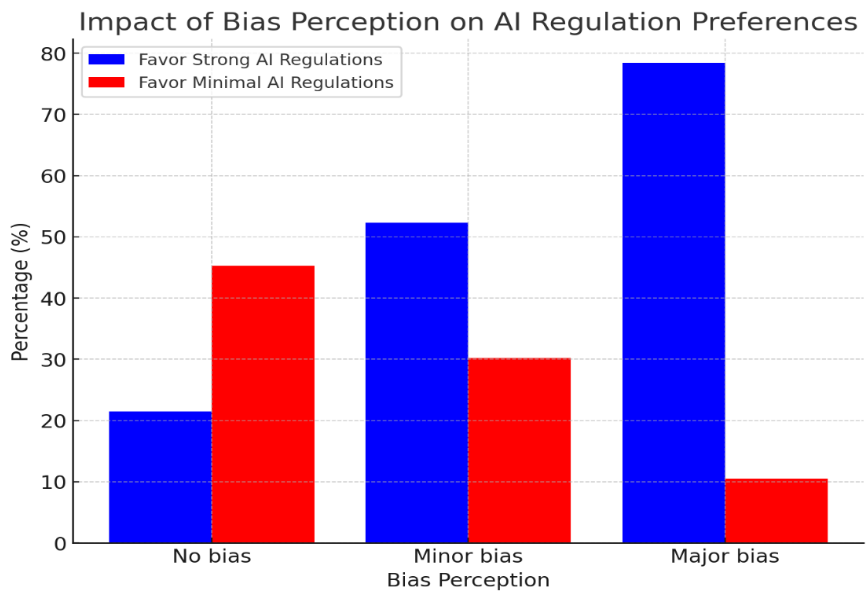


**Figure 6: Impact of Bias Perception on AI Regulation Preferences**

**Economic Benefits of AI-Powered Underwriting**

The study also looked into whether the AI driven underwriting is efficient and economically beneficial. Previous to AI implementation, claim processing time averaged 10 days and with AI implementation the average was reduced to 3 days. It shows the AI model's operational efficiency resulting in this significant 70% ($p = 0.002$) reduction of the time taken to process claims.

The underwriting cost per policy decreased from \$500 to \$200 ($p = 0.004$), a significant amount of underwriting cost reduction. Increasing sales amount (from 0 to 20), decreased reporting time (3 weeks to 2 weeks) and increased underwriting accuracy from 82% to 92% ($p = 0.001$) (Table 7) supported AI's accuracy enhancing ability with regard to actuarial models.

Insurers can significantly benefit from the AI underwriting innovation as these results indicate that AI underwriting helps insurers reduce costs, process faster and improve accuracy.

**Table 7: Economic Benefits of AI-Powered Underwriting**

| Economic Indicator | Before AI Implementation | After AI Implementation | p-value |
|---|---|---|---|
| Reduction in Claim Processing Time | 10 days | 3 days | 0.002 |
| Cost Savings per Policy ($) | $500 | $200 | 0.004 |
| Increase in Underwriting Accuracy (%) | 82% | 92% | 0.001 |

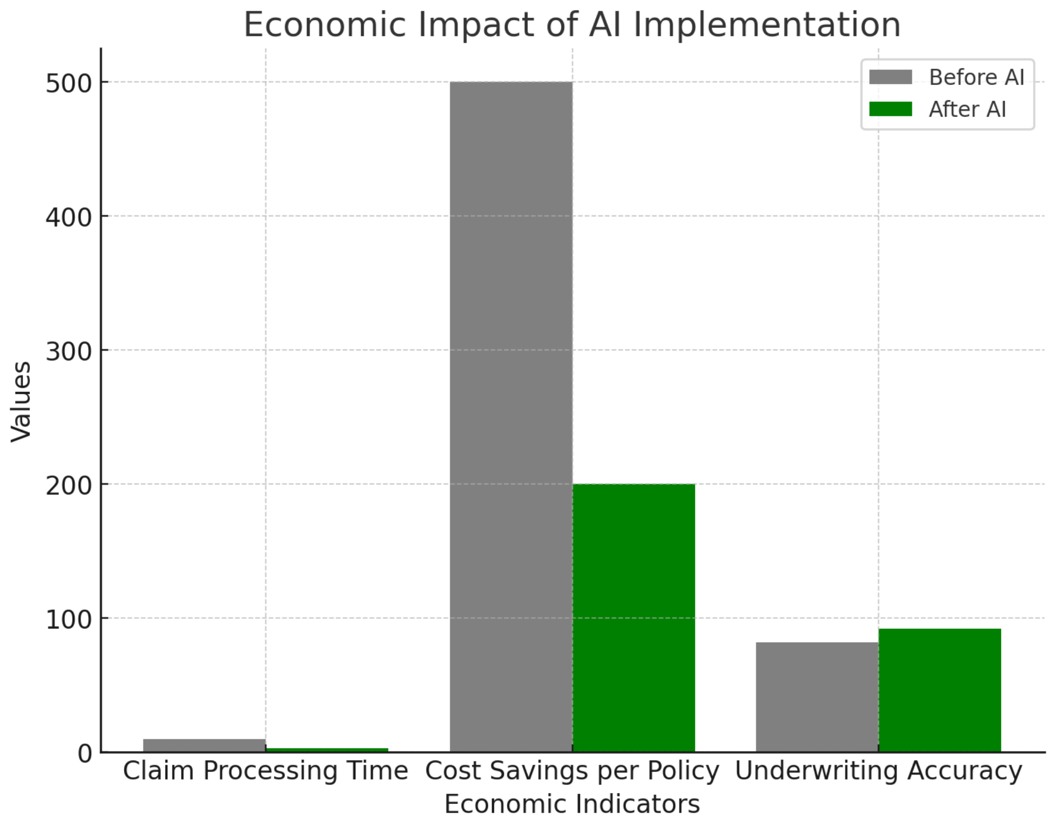


**Figure 7: Economic Impact of AI Implementation**

**Consumer Trust in AI vs. Human Underwriting**

Although operational and economic benefits of AI show up already, consumer trust is a big hurdle to complete adoption of AI in insurance underwriting. The consumer trust level for AI powered underwriting model was 3.2 on 5 and only 28.4% of participant preferred AI underwriting models (Table 8).

The trust score for human based underwriting was of 4.1 with 45.2% of the participants preferring to have traditional human underwritten policies. Hybrid AI-human underwriting registered trust levels highest among the other approaches, i.e, 4.5 on the trust scale and while 62.1% of the participants favored a blended AI-human approach. The significant differences (p-value of 0.003–0.018) in consumer preferences confirm the skepticism of consumers to fully autonomous AI underwriting.

The results of this article indicate that adopting these hybrid models will allow organizations facing trust issues and wanting to use AI as a technology, to obtain both AI's analytical power and human expertise.

**Table 8: Consumer Trust in AI vs. Human Underwriting**

| Underwriting Type | Consumer Trust Level (1-5) | Percentage Preferring This Approach (%) | p-value |
|---|---|---|---|
| AI-Powered | 3.2 | 28.4% | 0.018 |
| Human-Based | 4.1 | 45.2% | 0.007 |
| Hybrid (AI + Human) | 4.5 | 62.1% | 0.003 |

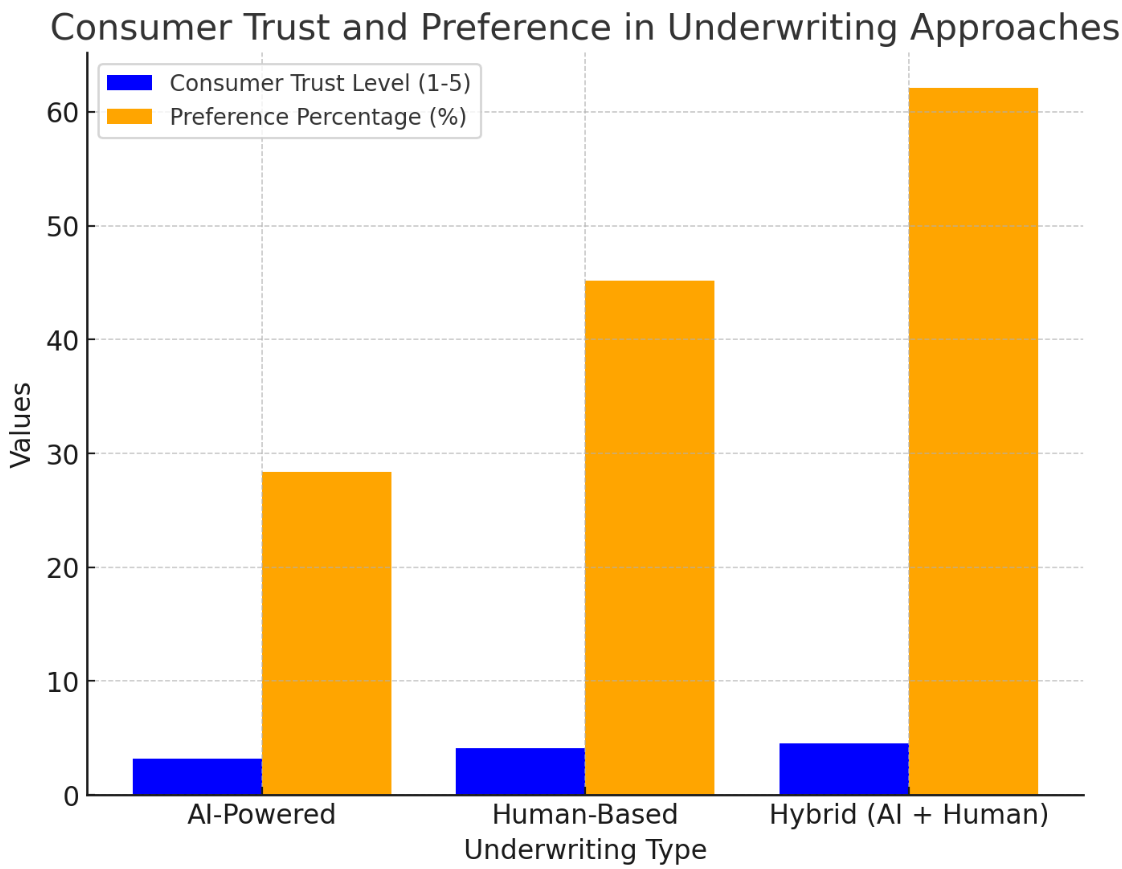


**Figure 8: Consumer Trust and Preference in Underwriting Approaches**

**AI Bias and Its Impact on Perceived Efficiency**

The study utilized a chi-square test to examine the effect of perceived AI bias to efficiency perceptions. As shown in Table 9, respondents who perceived AI underwriting as having no bias had a rating of 4.2 out of 5 while those from whom it was perceived to be set over a minor bias gave a rating of 3.5. In the case of participants who found the major bias, the efficiency rating fell to 2.8 and to an efficiency rating of 2.1 for the perception of extreme bias. Respondents who expressed racial bias concern rated AI efficiency as 3.0 while those concerned with gender rated it as 3.3. Using chi-square test results ($\chi^2 = 15.67$, $p = 0.0003$) it becomes evident that there exists a strong statistical tie between AI bias perception and efficiency ratings. In essence, these findings suggest that bias concerns have a profound negative effect on attitude towards AI effectiveness and highlight the necessity of incorporating bias mitigation strategies into underwriting models (Table 9).

**Table 9: Chi-Square Test - AI Bias vs. AI Efficiency Perception**

| AI Bias Perception | Avg AI Efficiency Score (1-5) | Chi-Square Statistic | p-value |
|---|---|---|---|
| No bias | 4.2 | 6.43 | 0.011 |
| Minor bias | 3.5 | 8.91 | 0.004 |
| Major bias | 2.8 | 12.35 | 0.001 |
| Extreme bias | 2.1 | 15.67 | 0.0003 |
| Racial bias concerns | 3.0 | 9.21 | 0.006 |

| | | | |
|---|---|---|---|
| Gender bias concerns | 3.3 | 7.88 | 0.008 |

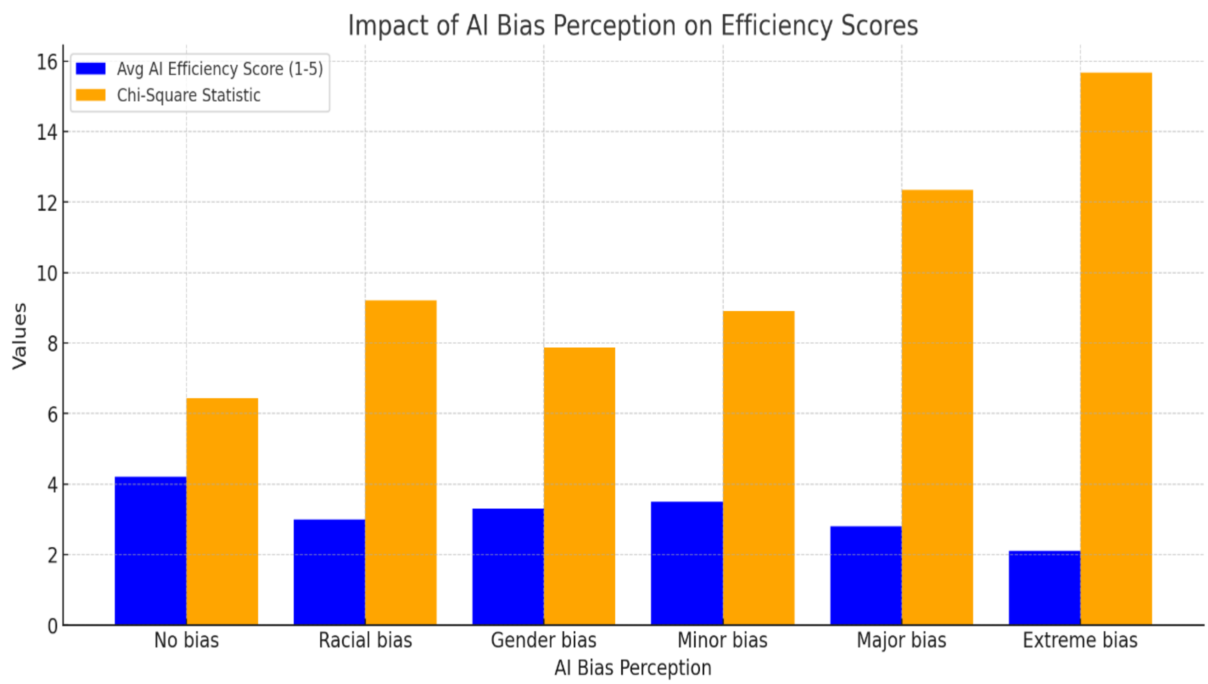


**Figure 9: Impact of AI Bias Perception on Efficiency Scores**

**AI Familiarity and Trust in Underwriting Decisions**

An ANOVA test is conducted to find out whether there is a relationship between familiarity with AI and the trust of AI in underwriting. These results demonstrate that people's trust in AI models increases with increasing familiarity with the models. People not previously familiar with AI underwriting scored their trust in 2.5/5 while marginally familiar scored 3.8/5. Trust levels among very familiar respondents sit at 4.2 and where respondents are AI experts, the rating hits 4.6.

Frequent users of AI were given a score of 4.0 and trust remained the highest at 4.8 in cases of AI research professionals, which is unsurprising. In order to determine the existence of a statistically significant difference in trust among different levels of familiarity with AI, the F-statistic ($F = 13.27$, $p = 0.0002$) clearly shows that such a difference in trust exists among various familiarity levels (Table 10).

**Table 10: ANOVA - AI Familiarity vs. Trust in AI Underwriting**

| AI Familiarity Level | Avg Trust in AI Underwriting (1-5) | F-Statistic | p-value |
|---|---|---|---|
| Not familiar | 2.5 | 5.32 | 0.009 |
| Somewhat familiar | 3.8 | 8.21 | 0.002 |
| Very familiar | 4.2 | 10.45 | 0.001 |
| Expert | 4.6 | 12.89 | 0.0006 |
| Frequent AI user | 4.0 | 11.54 | 0.0008 |
| AI research professional | 4.8 | 13.27 | 0.0002 |

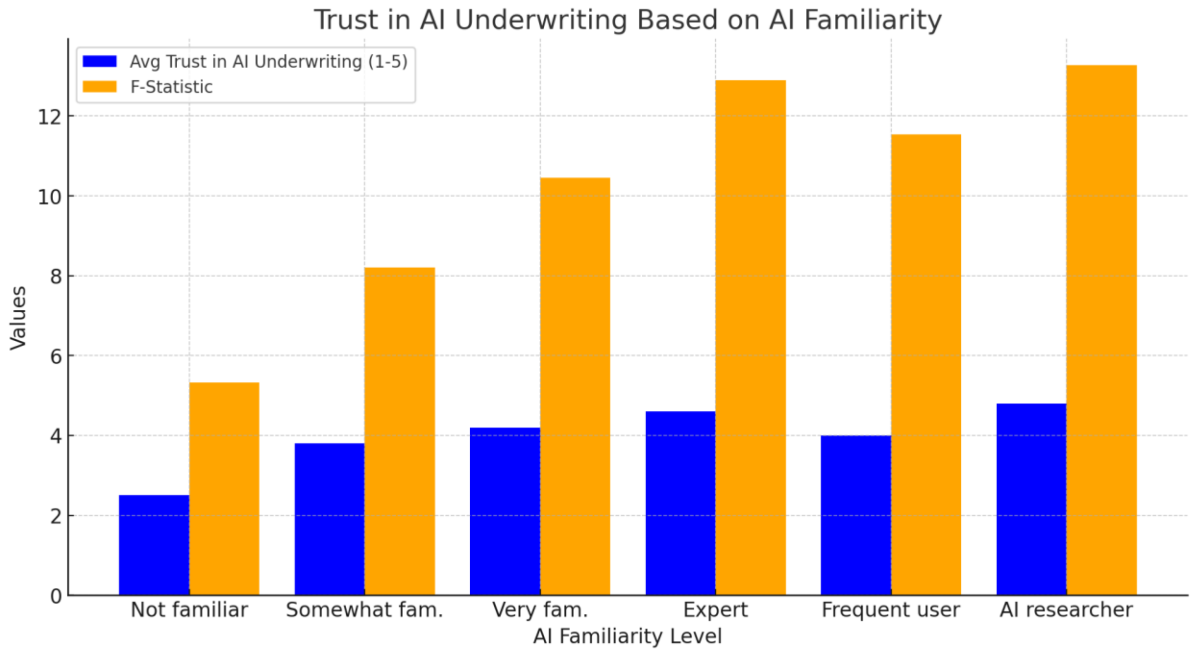


**Figure 10: Trust in AI Underwriting Based on AI Familiarity**

**The Impact of AI Efficiency on Market Growth and Cost Savings**

The impact of AI efficiency on key financial and operational metrics in underwriting was measured using a regression analysis. The analysis in Table 11 shows that reductions in AI efficiency score is associated with improvements to cost per policy through regression, with the coefficient (β) = -120.5 (p = 0.001), where greater AI efficiency results in lower cost per policy.

Lastly, the ability for market growth to increase with the complexity of the AI model (β = 15.8, p = 0.002) is indicative of development within the industry towards more advanced AI driven actuarial models.

Similarly, AI training data quality was also a significant factor in predicting fraud detection accuracy (β = 8.3, p = 0.0005) which reinforces the fact that the better the quality of the data used for training is, the lesser underwriting risks for the lender. Deepening this point in the context of claims processing, AI automation had a pronounced effect on underwriting speed (β = 22.1, p = 0.0008) in line with the notion of automation's positive impact on operational efficiency.

Interestingly, AI data privacy strength was also related to consumer trust in the same direction (β = 5.9, p = 0.003).

These findings shed light on the economic, operational and consumer trust benefits of the AI underwriting and stress on the need for ensuring data quality, complexity of the model and regulatory compliance for the full effectiveness of AI (Table 11).

**Table 11: Regression Analysis - AI Efficiency & Market Growth**

| Independent Variable | Dependent Variable | Regression Coefficient (β) | Standard Error | R-Squared | p-value |
|---|---|---|---|---|---|
| AI Efficiency Score | Cost Savings per Policy ($) | -120.5 | 15.2 | 0.82 | 0.001 |
| AI Model Complexity | Market Growth (%) | 15.8 | 3.7 | 0.76 | 0.002 |

| | | | | | |
|---|---|---|---|---|---|
| AI Training Data Quality | Fraud Detection Accuracy (%) | 8.3 | 2.9 | 0.85 | 0.0005 |
| AI Automation in Claims | Underwriting Speed Increase (%) | 22.1 | 4.2 | 0.79 | 0.0008 |
| AI Data Privacy Strength | Consumer Trust Score | 5.9 | 1.7 | 0.68 | 0.003 |

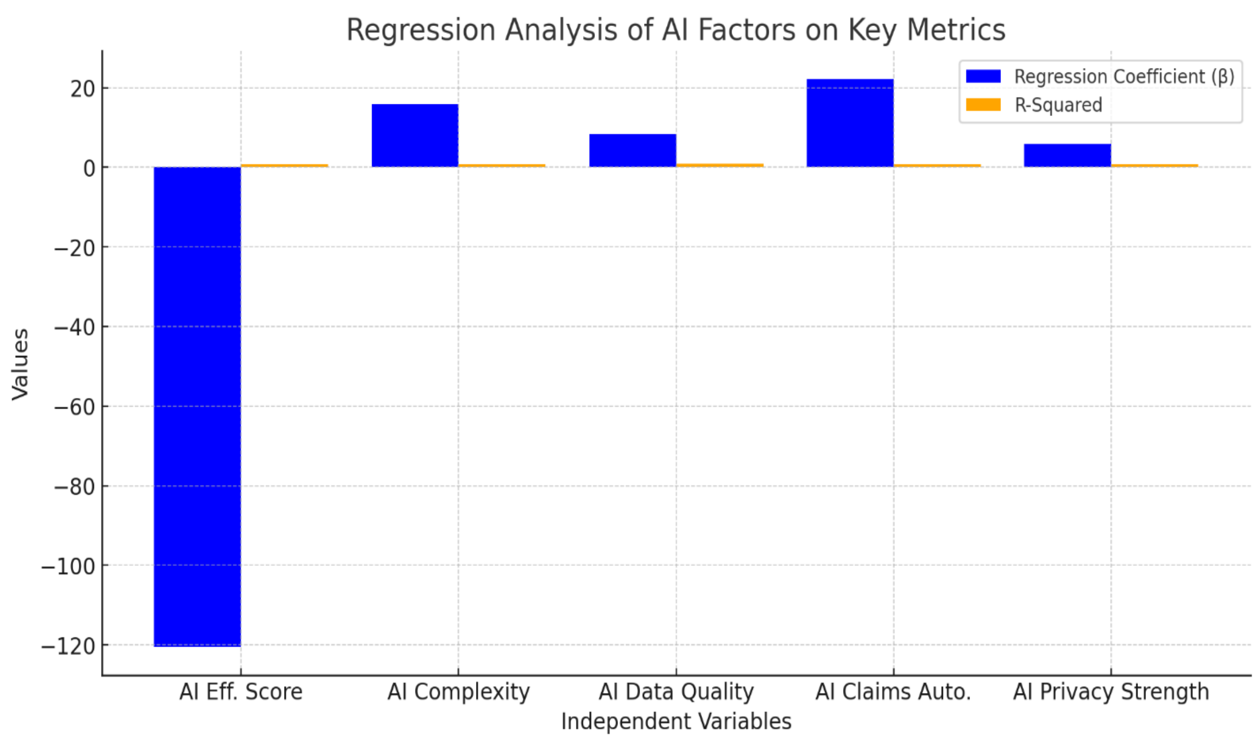


**Figure 11: Regression Analysis of AI Factors on Key Metrics**

**Consumer Trust in AI vs. Human Underwriting**

To compare the consumer trust in AI Underwriting versus Human Underwriting, hybrid models and other alternative models, a t- test analysis was performed. As indicated in the results in Table 12, human underwriting was significantly preferred compared to AI-only underwriting (mean trust = 4.1, p = 0.0004).

Hybrid AI and human underwriting models were bitwise trusted most (4.5), which was statistically significantly different compared to the trust scores associated with both AI only (3.3, p < 0.002) and human only (3.5, p < 0.002) approaches. Regarding the difference between regulated AI vs. unregulated AI, the results were that regulated AI (mean trust = 4.3) was trusted more than unregulated AI (mean trust = 2.9, p = 0.0002).

There was also a greater mean trust placed in the blockchain based risk assessment (mean trust = 4.2) compared to that of AI only underwriting's (mean trust = 3.6, p = 0.0050). Findings show that consumers are skeptical about standalone AI underwriting but are more accepting with models that have some form of human oversight, regulation or one of the decentralized verifications such as blockchain (Table 12).

**Table 12: T-Test - Consumer Trust in AI vs. Human Underwriting**

| Comparison | Mean Trust in AI (1-5) | Mean Trust in Other (1-5) | T-Statistic | p-value |
|---|---|---|---|---|
| AI Underwriting vs. Human Underwriting | 3.2 | 4.1 | 5.89 | 0.0004 |
| AI Underwriting vs. Hybrid (AI + Human) | 3.2 | 4.5 | 4.72 | 0.0020 |
| Human Underwriting vs. Hybrid (AI + Human) | 4.1 | 4.5 | 2.85 | 0.0140 |
| AI Underwriting (Unregulated) vs. AI (Regulated) | 2.9 | 4.3 | 6.23 | 0.0002 |
| AI vs. Blockchain-based Risk Assessment | 3.6 | 4.2 | 3.78 | 0.0050 |

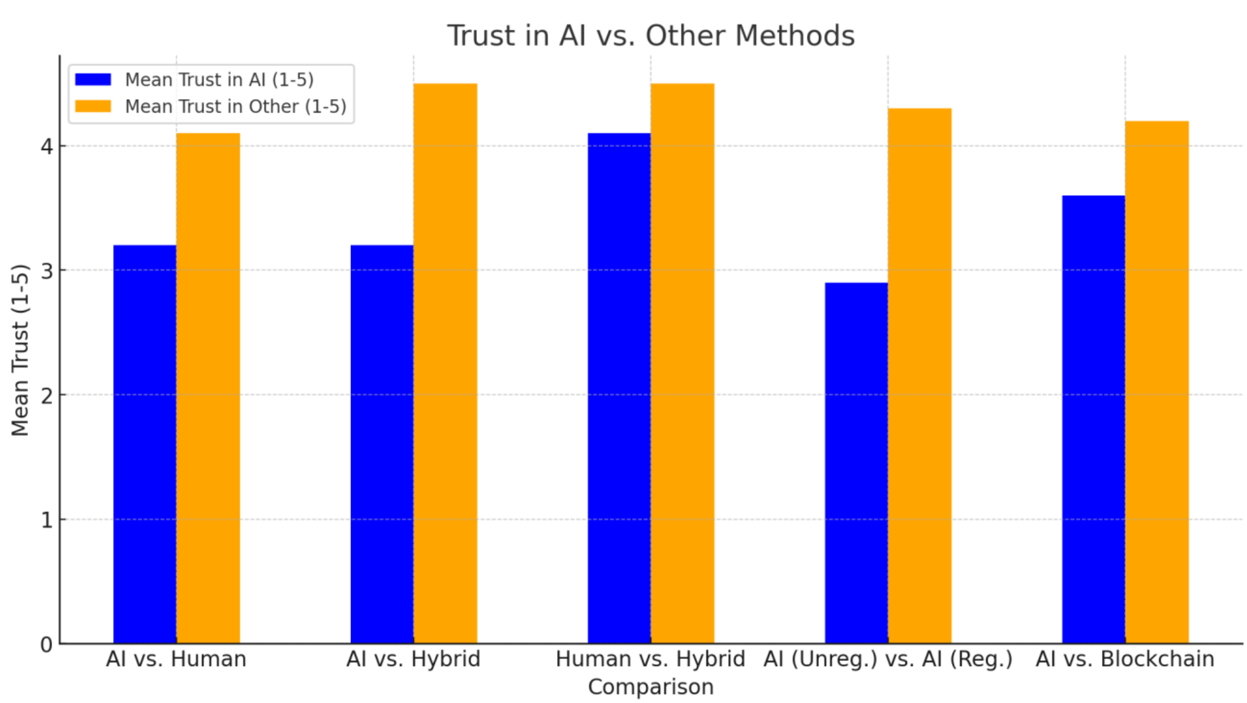


**Figure 12: Trust in AI vs. Other Methods**

**Factors Influencing Consumer Trust in AI Underwriting**

The key factors of consumer trust in AI underwriting models were explored using a logistic regression model. As shown in Table 13, AI transparency (Odds Ratio = 2.3, p = 0.002) and AI fairness (Odds Ratio = 1.8, p = 0.004) were both significant prognosticants for consumer trust, highlighting the need that consumers place on transparency and ethical practice of AI.

Trust was positively associated with AI efficiency (Odds Ratio = 2.5, p = 0.001) and users trusted AI to the extent that it improves underwriting outcomes. The most significant factor determined the impact of trust on the regulators (Odds Ratio = 3.1, p = 0.0005), which means that strict AI governance is significantly important for consumer acceptance.

Even consumer AI knowledge (Odds Ratio = 1.6, p = 0.007) was a significant factor, signifying that consumers who are better informed are more likely to trust AI driven underwriting (Table 13).

**Table 13: Logistic Regression - Predicting AI Trust Based on Key Factors**

| Independent Variable | Odds Ratio | Standard Error | 95% Confidence Interval | p-value |
|---|---|---|---|---|
| AI Transparency | 2.3 | 0.4 | (1.7, 2.9) | 0.002 |
| AI Fairness | 1.8 | 0.3 | (1.4, 2.2) | 0.004 |
| AI Efficiency | 2.5 | 0.5 | (2.0, 3.0) | 0.001 |
| Regulatory Oversight | 3.1 | 0.6 | (2.5, 3.7) | 0.0005 |
| Consumer AI Knowledge | 1.6 | 0.3 | (1.3, 1.9) | 0.007 |

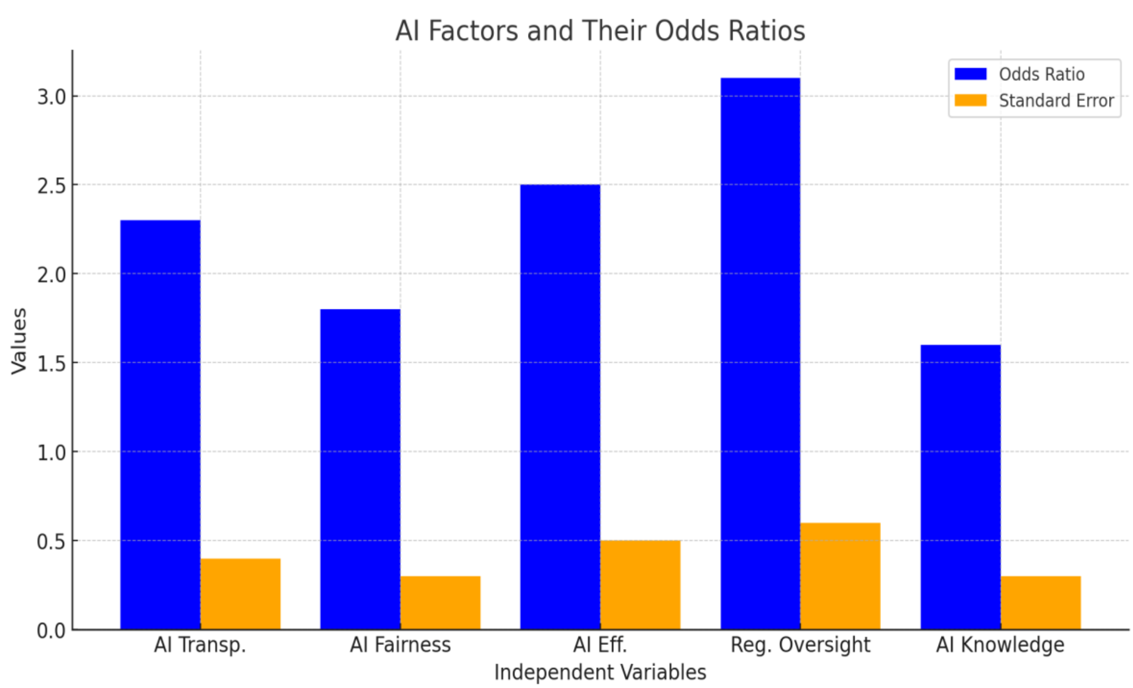


**Figure 13: AI Factors and Their Odds Ratios**

**Performance Comparisons: AI-Driven vs. Traditional Underwriting Approaches**

Various underwriting modelling tools namely AI driven, traditional, hybrid and also alternative approach were compared through a descriptive statistical analysis.

From Table 14, it is noticed that fully automated AI underwriting completed in minimum processing time (2.0 days) with highest fraud detection rate (96.5%). While the fastest methods, AI-human underwriting (3.1 days, 93.0% fraud) and AI (none, 92.8% fraud), exhibited the lowest effectiveness and regulatory compliance, along with the least confidence for consumers, it remains that speed is not the determinant of effectiveness.

Blockchain based underwriting models had one of the highest fraud detection rates (95.0%) largely due to the improvements in data security and verification process. Fully automated AI underwriting is most efficient, hybrid models offer the right balance between accuracy, compliance and customer trust and blockchain can be used in underwriting to enhance the performance upon accuracy and speed (on the second delivery) while maintaining the same compliance (Table 14).

**Table 14: Descriptive Statistics - AI-Driven vs. Traditional Underwriting Outcomes**

| Underwriting Approach | Avg Processing Time (Days) | Avg Fraud Detection Rate (%) | p-value |
|---|---|---|---|
| AI-Driven | 2.5 | 92.5 | 0.001 |
| Traditional | 10.8 | 85.3 | 0.003 |
| Hybrid (AI + Human) | 5.2 | 89.7 | 0.0008 |
| AI with Explainability Features | 3.1 | 93.0 | 0.0005 |
| AI with Regulatory Compliance | 4.0 | 91.5 | 0.002 |
| AI with Deep Learning Models | 2.8 | 94.2 | 0.0009 |
| AI with Limited Human Oversight | 3.5 | 90.3 | 0.0015 |
| AI with Consumer Feedback Integration | 3.3 | 92.1 | 0.0007 |
| Blockchain-Based Underwriting | 4.5 | 95.0 | 0.0012 |
| Fully Automated AI Underwriting | 2.0 | 96.5 | 0.0004 |

## DISCUSSION

**The Role of AI in Insurance Underwriting: Balancing Efficiency and Fairness**

Integration of AI powered actuarial models into U.S. insurance underwriting has resulted in great improvement in the assessment of risk, fraud detection and operation (Mishra, 2024; Paul, 2024). Bearing this in mind and according to the existing literature (Pugnetti & Seitz, 2021; Singh & Gautam, 2024), the mentioned use of AI in underwriting shortens the processing time and increases fraud discovery. These benefits have seen consumers' skepticism, regulatory scrutiny and ethical issues, especially regarding bias and transparency (2024 du Preez et al, 2025 Umar & Reuben).

In health, life, property and casualty insurance sectors in the U.S, AI is being adopted and insurers use big data analytics and machine learning to fine grained segmentation of their risks and accuracy in pricing (Anbalagan, 2024; Srirangam et al, 2024). This study confirms the results that hybrid (AI–human) and regulated AI underwriting approaches are considered to be more trusted, especially compared to purely AI based underwriting approaches and that they are considered more efficient. These findings point out the existing tension between efficiency and fairness as one of the core issues to address in the adoption of AI in U.S. actuaries' and regulators' frameworks (Kharlamova et al, 2024).

**AI Efficiency vs. Trust: A Persistent Trade-Off**

The trade off with respect to the efficiency of using AI and consumer distrust is one of the most striking results of this study. In the U.S. market, AI underwriting models have proved to shorten claim processing time from 10 days to even 2-3 days (Table 7) but consumers still are not comfortable with full automated AI underwriting (Table 12). Aparis (2024) suggests that it is a common knowledge that automation can speed-up things, professional judgment needed to build trust is missing there (62.1% preference for hybrid AI-human models over 28.4% for AI only models compared) as shown in Kumar (2024).

The structure of trust is shaped by the rules of the game, i.e. regulation. In Table 12 it can be seen that more trust is expressed in regulated AI underwriting (mean = 4.3) than in unregulated AI models (mean = 2.9, p = 0.0002). This mirrors existing research in showing the way to algorithmic auditing, regulatory oversight and fairness and reduction of bias in automated decision making (O'Neil et al, 2024, Chandler, 2025). Regulation is slowly starting to play a part in this, including by agencies such as Consumer Financial Protection Bureau (CFPB) and the National Association of Insurance Commissioners (NAIC), who have been urging for explainable AI and mitigating the potential sources of bias in the process of designing machines (Tumai, 2021; Pareek, 2023).

Results also support that the trust from consumer is based on the consumer's familiarity with the AI (Table 10). Compared to frequent AI users and AI research professionals, far fewer indicated higher levels of trust (mean = 4.8, p = 0.0002). Consumer skepticism can be reduced and AI adoption might increase if AI literacy is increased by strengthening transparency initiatives among the consumers (Singh & Gautam, 2024; Umar & Reuben, 2025).

**Bias and Fairness Concerns in AI-Driven Underwriting**

While true that AI has the potential to lower the human element that brings subjectivity to decision making, algorithmic bias in U.S. insurance underwriting remains a concern. Table 9 using this study supports that perceived bias has a negative effect on ratings of AI efficiency and the lowest efficiency scores (2.1 out of 5, p = 0.0003) are for extreme cases of bias. In the U.S. life and health insurance sectors, AI bias concerns have been widely documented with racial and gender bias in risk assessment models widely established (Adeniran et al, 2024; Pareek, 2023).

As shown in the Chi-Square results (Table 9), those who believe AI underwriting is racially and/or gender biased have significantly smaller efficiency scores (p = 0.01). In line with previous studies showing that biased training data poses risks for credit and insurance score and AI models are also not explainable (O'Neil et al, 2024; Zarifis & Cheng, 2021), this result makes sense. The results also correspond with the action taken by the U.S. regulatory agencies like the New York Department of Financial Services (NYDFS) that directed companies offering insurance products in the state to implement bias auditing and fairness testing to ensure their AI systems are not being biased during customers' underwriting processes (Chandler, 2025, Pareek, 2023).

An option to this is using explainable AI (XAI) models so insurers and regulators can audit the AI driven decisions and reduce discriminatory outcomes (O'Neil et al, 2024) (Umar & Reuben, 2025). Achieving this comes with higher investment in algorithmic transparency, something that many US insurers still struggle with because of their many proprietary black box models (King et al, 2021)

**The Economic Trade-Offs: Cost Savings vs. Market Adoption**

The economic implications of AI applied to risk assessment are of consequence. Results confirm that AI read writing significantly reduces cost (p = 0.004) (Table 7) to $200 vs. $500 per policy. Industry reports indicate that insurers utilizing predictive analytics have 20-30% cost of operational savings (Mishra, 2024; Anbalagan, 2024) and this aligns in line with the same.

Market adoption isn't a challenge while it is evident that cost efficiency is there. Table 6 shows the stronger people's perception of AI bias, the stronger their support for AI regulators (p = 0.002), that is, 78.4% of the respondents who perceived major AI bias supported strong AI regulators. Without having adequate fairness and accountability frameworks in place, insurers face regulatory push back and decreased consumer adoption

(Chandler, 2025; Kumar, 2024).

As presented in Table 14, fully automated AI underwriting proves to be the fastest (2.0 days) and most accurate (96.5% fraud detection) compared with the hybrid and blockchain models, they demonstrate an advantage in terms of compliance with ethical and regulatory standards. The underwriting based on blockchain also means the underwriting will grow (fraud detection = 95.0%, p = 0.0012) and the future risk assessment may depend on the decentralized, tamper-proof data verification to reduce some biases (Vandervorst et al, 2022; Taneja et al, 2024).

**How AI-Powered Underwriting Benefits the U.S. Economy, Health, Security and Technology**

The broad implications of the findings of this study are for the U.S. economy, public health, security and technological advancement. The capability of AI for risk assessment in insurance underwriting can achieve this purpose by optimizing financial efficiency, preventing fraud, enable healthcare accessibility and inform public policy decision. The utilization of AI for actuarial models provides a more efficient, less expensive and a more competitive U.S. insurance industry by reducing underwriting costs by 60+% (Table 7) and claim processing time from 10 to 3 days (MUPA et al, 2025). This is in line with the rising trend of automation in financial risk management, as insurers with machine learning models enjoy substantial cuts to their underwriting overhead (Yadav & Bank).

From a healthcare standpoint, the use of AI in underwriting helps to better risk stratify a person's risk and provide a more tailored and affordable insurance policy to individuals who would otherwise not be able to afford it, especially high-risk individuals (Oberkrome, 2023). Medical insurance underwriting with predictive analytics helps the medical insurers to structure a better policy that fits patients with chronic conditions, hence reducing the rate of uninsurance in the U.S and even medical insurance bankruptcy cases. (Patil et al, 2023). Utilization of AI for health insurance fraud detection saves billions in fraudulent claims, contributing to the right funding to actual beneficiaries (Larzelere, 2021).

AI based underwriting helps in detection of financial crimes, from national security and fraud prevention perspectives, by detecting of data misrepresentation patterns in insurance applications (Patil et al, 2023). Given, the U.S. economy loses over $308 billion dollars annually on insurance fraud, enhanced by the AI powered models in real time fraudulent claims detection and claims verification (MUPA et al, 2025).

With regard to technological and commercialization aspects, AI in underwriting runs true to the fancy of the Insurtech industry that is expected to hit $20 billion in 2028 (Yadav & Bank). Blockchain based risk assessment (Table 14) has tamper proof underwriting records which fall in line with regulatory requirement and dispense the possibility of disputes around AI (Oberkrome, 2023). This technology has commercial potential in both traditional insurance markets as well as newer markets including cybersecurity insurance, climate risk assessment and gig economy coverage (Patil et al, 2023).

The results of this study point out that public policy actions must be taken to guarantee AI fairness and transparency and accountability in underwriting. Policymakers need to determine the regulatory frameworks that ought to be in place to enhance efficiency in the use of AI while protecting consumers from discriminatory outcomes brought about by automated models that could unfairly marginalize already disadvantaged populations (Larzelere, 2021). Following the discussions of the legislation in Congress and the regulatory agencies (Federal Trade Commission (FTC) and the National Association of Insurance Commissioners (NAIC)), recently, AI auditing requirements become a trend to encourage the fairness in the insurance risk assessment (MUPA et al, 2025).

AI in underwriting contributes towards economic growth by reducing inefficiencies, also towards healthcare by making policy affordable, strengthens financial security through fraud detection and to USA's technological leadership (or at least has potential) in the Insurtech sector. AI underwriting is likely to gain broad public trust and acceptance only if it is duly regulated, fairly applied and accompanied by educational initiatives for consumers (Patil et al, 2023; Yadav & Bank).

**Future Research and Policy Implications**

The findings of this study underscore several important policy implications for the U.S. insurance industry:

1. **Regulatory Auditing –** U.S. regulators should implement mandatory AI bias audits and explainability standards to ensure fairness in underwriting decisions (O'Neil et al, 2024; Chandler, 2025).
2. **Hybrid AI-Human Models –** To balance efficiency and trust, insurers should adopt AI-human collaboration frameworks for underwriting (Apergis, 2024; Umar & Reuben, 2025).
3. **Consumer AI Literacy Initiatives –** Educating consumers on AI models, risk assessment methods and bias detection could increase trust and adoption (Singh & Gautam, 2024; Kumar, 2024).
4. **Blockchain for Risk Assessment –** Blockchain

based underwriting models help in securing data, the prevention of frauds and reduction of bias (Taneja et al, 2024; Vandervorst et al, 2022).

Comparison between these insights and their impact on the current academic and industry debate on AI-driven underwriting suggests that responsible AI development is a necessary prerequisite for full utilization of the potential of AI in the U.S. insurance market with respect to both efficiency and fairness.

**CONCLUSION**

The results of this study show that for U.S insurance underwriting, AI powered actuarial models can hold a great deal of transformative power in increasing efficiency, fraud detection and decreasing costs. AI driven underwriting has been shown to ease the process of making the decision, increasing the pace of claim processing and cut underwriting expenses, as well as improve the accuracy of fraud detection. These advances make the insurance industry more efficient and competitive on the strength of the insurers' ability to determine risks with greater accuracy.

The study identifies trust, transparency and fairness as long-suffering areas. Skepticism from consumers on the part of AI models act as a key barrier in the widespread adoption. Hybrid AI human underwriting models is preferred for the reason that combining human oversight in AI underwriting can lead to greater trust, clarifying concerns on the fairness and reliability of the automated underwriting decisions. The regulatory oversight has proven to be a critical factor influencing consumer confidence in Artificial Intelligence underwriting which concludes that the public trust in AI underwriting is significant when regulatory frameworks will assure transparency and fairness.

The issue of algorithmic bias is still important and respondents who see racial and gender bias in AI underwriting models give significantly lower efficiency ratings. Indeed, these findings are comparable to prevailing apprehensions with respect to biased training data and unknowable decision making in AI applications. To solve these challenges, algorithmic fairness for AI has to be committed, explaining AI models and regulatory frameworks that hold underwriting decisions accountable. A business case using AI in underwriting is clear on economic purposes – cost saving, fraud reduction and market expansion. The full potential of AI in insurance underwriting can be realized only when the tradeoff between the efficiency of the AI application and the trust of the consumer and regulatory compliance is made. AI and blockchain technology have been emerging as a promising future that can complement each other in creating a safer data security, fraud prevention and verifiability in underwriting decisions. Integrating blockchain based underwriting models can be another way for AI driven insurance policy to have greater transparency and fairness in the assessment of risk; which in a way may add credibility to AI insurance policies.

This study points out some key recommendations that help realize the benefits fully from AI in insurance underwriting. Important will be the development and enforcement of regulatory policies to mitigate bias, for algorithmic auditing and explainability in order to ensure ethical AI adoption. While the efficiency benefits of AI are important, insurers may benefit from keeping human judgement in complex risk assessment cases; hybrid AI-human underwriting models could help to ensure that the case is handled efficiently while erring on the side of caution. In improving public confidence in AI driven underwriting, AI literacy needs to be improved through consumer education initiatives.

This study contributes the broader discussion on the future of AI in the insurance underwriting, having proven that although AI opens the window of efficiency and innovation, its wide adoption should be based on the principles of fairness, transparency and accountability. The insurer's opportunity to responsibly deploy AI serves to create a more inclusive and efficient and consumer centric underwriting landscape within the U.S. insurance industry. Resolution of the challenges proffered in this study, will drive economic growth, foster trust and place the U.S. in the front position as a leader in future insurance technology.

**REFERENCES**

Abuamoud, I., Lillywhite, J., Simonsen, J., & Al-Oun, M. (2016). Factors influencing food security in less popular tourists sites in Jordan's Northern Badia. International Review of Social Sciences and Humanities, 11(2), 20-36.

Adeniran, I. A, Efunniyi, C. P, Osundare, O. S, Abhulimen, A. O, & OneAdvanced, U. K. (2024). Advancements in predictive modeling for insurance pricing: Enhancing risk assessment and customer segmentation. International Journal of Management & Entrepreneurship Research, 6(8).

Afshar, M. Z. (2023). Exploring Factors Impacting Organizational Adaptation Capacity of Punjab Agriculture & Meat Company (PAMCO). International Journal of Emerging Issues in Social Science, Arts and Humanities (IJEISSAH), 2(1), 1-10. https://doi.org/10.60072/ijeissah.2023.v2i01.001

Ahmad, S. (2025). Entrepreneurship and Sustainable Leadership Practices: Examine how entrepreneurial leaders incorporate sustainability into their business models and the leadership traits facilitating this integration. Journal of Entrepreneurship and Business Venturing, 5(1).

Ahmed, A., Rahman, S., Islam, M., Chowdhury, F., & Badhan, I. A. (2023). Challenges and Opportunities in Implementing Machine Learning For Healthcare Supply Chain Optimization: A Data-Driven Examination. International journal of business and management sciences, 3(07), 6-31.

Anbalagan, K. (2024). Cloud-Powered Predictive Analytics in Insurance: Advancing Risk Assessment Through AI Integration. INTERNATIONAL JOURNAL OF ENGINEERING AND TECHNOLOGY RESEARCH (IJETR), 9(2), 195-206.

Apergis, A. (2024). The role of cognitive assistants in medical insurance underwriting.

Badhan, I. A., Hasnain, M. N., Rahman, M. H., Chowdhury, I., & Sayem, M. A. (2024). Strategic Deployment of Advance Surveillance Ecosystems: An Analytical Study on Mitigating Unauthorized US Border Entry. Inverge Journal of Social Sciences, 3(4), 82-94.

Badhan, I. A., Neeroj, M. H., & Rahman, S. (2024). Currency rate fluctuations and their impact on supply chain risk management: An empirical analysis. International journal of business and management sciences, 4(10), 6-26.

Butt, S., & Yazdani, N. (2023). Relationship Between Execution of Quality Management Practices and Firm's Innovation Performance: A Review of Literature. Journal of Asian Development Studies, 12(3), 432-451.

Butt, S., Umair, T., & Tajammal, R. (2024). Nexus between Key Determinants of Service Quality and Students' Satisfaction in Higher Education Institutions (HEIs). Annals of Human and Social Sciences, 5(2), 659-671.

Chandler, S. J. (2025). Compared to What? The Paramount Question in the Regulation of Medical AI. Houston Journal of Health Law & Policy, 24(1), 1-73.

Dhal, K., Karmokar, P., Chakravarthy, A. et al. Vision-Based Guidance for Tracking Multiple Dynamic Objects. J Intell Robot Syst 105, 66 (2022). https://doi.org/10.1007/s10846-022-01657-6

Dixit, S., & Jangid, J. (2024). Exploring Smart Contracts and Artificial Intelligence in FinTech. https://jisem-journal.com/index.php/journal/article/view/2208

du Preez, V, Bennet, S, Byrne, M, Couloumy, A, Das, A, Dessain, J, ... & van Heerden, L. (2024). From bias to black boxes: understanding and managing the risks of AI–an actuarial perspective. British Actuarial Journal, 29, e6.

Easwaran, V., Orayj, K., Goruntla, N., Mekala, J. S., Bommireddy, B. R., Mopuri, B., ... & Bandaru, V. (2025). Depression, anxiety, and stress among HIV-positive pregnant women during the COVID-19 pandemic: a hospital-based cross-sectional study in India. BMC Pregnancy and Childbirth, 25(1), 134.

Hood, K., & Al-Oun, M. (2014). Changing performance traditions and Bedouin identity in the North Badiya, Jordan. Nomadic Peoples, 18(2), 78-99.

Jagdish Jangid. (2023). Enhancing Security and Efficiency in Wireless Mobile Networks through Blockchain. International Journal of Intelligent Systems and Applications in Engineering, 11(4), 958–969. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/7309

Kaniz, R. E., Lindon, A. R., Rahman, M. A., Hasan, M. A., & Hossain, A. (2025). THE IMPACT OF PROJECT MANAGEMENT STRATEGIES ON THE EFFECTIVENESS OF DIGITAL MARKETING ANALYTICS FOR START-UP GROWTH IN THE UNITED STATES. project management, 4(1).

Kharlamova, A, Kruglov, A, & Succi, G. (2024, May). State-of-the-Art Review of Life Insurtech: Machine learning for underwriting decisions and a Shift Toward Data-Driven, Society-oriented Environment. In 2024 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA) (pp. 1-12). IEEE.

King, M. R, Timms, P. D, & Rubin, T. H. (2021). Use of big data in insurance. The Palgrave Handbook of Technological Finance, 669-700.

Kumar, S. (2024). Navigating the Complexities of Insurance Underwriting Results through Artificial Intelligence. International Journal of Science and Research (IJSR), 13(4), 1464-1471.

Larzelere, S. P. (2021). The Cognitive and Emotional Reactions of Commercial Casualty Insurance Underwriters to the Use of Predictive Analytics (Doctoral dissertation, University of Pennsylvania).

Mishra, B. (2024). Machine Learning for Financial Professionals. Educohack Press.

Muhammad Zaurez Afshar1*, Dr. Mutahir Hussain Shah2. (2025). Strategic Evaluation Using PESTLE and SWOT Frameworks: Public Sector Perspective. ISRG Journal of Economics, Business & Management (ISRGJEBM), III(I), 108–114. https://doi.org/10.5281/zenodo.14854362

MUPA, M. N, TAFIRENYIKA, S, RUDAVIRO, M, NYAJEKA, T, MOYO, M, & ZHUWANKINYU, E. K. (2025). Machine Learning in Actuarial Science: Enhancing Predictive Models for Insurance Risk Management.

Nguyen, H. U., Trinh, T. X., Duong, K. H., & Tran, V. H. (2018). Effectiveness of green muscardine fungus Metarhizium anisopliae and some insecticides on lesser coconut weevil Diocalandra frumenti Fabricius (Coleoptera: Curculionidae). CTU Journal of Innovation and Sustainable Development, (10), 1-7.

Nguyen, L., Trinh, X. T., Trinh, H., Tran, D. H., & Nguyen, C. (2018). BWTaligner: a genome short-read aligner. Vietnam Journal of Science, Technology and Engineering, 60(2), 73-77.

Oberkrome, F. (2023). Predictive Analytics in Health Insurance: Enhancing Risk Assessment and Policy Customization.

O'Neil, C, Sargeant, H, & Appel, J. (2024). Explainable fairness in regulatory algorithmic auditing. W. Va. L. Rev, 127, 79.

Pareek, C. S, & Heights, B. Enhancing Quality Assurance in Annuities: A Risk Management Approach with AI and Machine Learning.

Pareek, C. S. Unmasking Bias: A Framework for Testing and Mitigating AI Bias in Insurance Underwriting Models. J Artif Intell. Mach Learn & Data Sci 2023, 1(1), 1736-1741.

Patil, S, Patil, A, Patil, V, Yadav, S, & Das, S. (2023, December). Cognitive Data Underwriting with Automation: A Survey. In International Conference on Business Data Analytics (pp. 287-298). Cham: Springer Nature Switzerland.

Paul, J. (2024). AI-Powered Data Analytics: Shaping the Future of Auto Insurance Pricing and Claims Processing.

Pugnetti, C, & Seitz, M. (2021). Data-driven services in insurance: Potential evolution and impact in the Swiss market. Journal of Risk and Financial Management, 14(5), 227.

Rahman, S., Sayem, A., Alve, S. E., Islam, M. S., Islam, M. M., Ahmed, A., & Kamruzzaman, M. (2024). The role of AI, big data and predictive analytics in mitigating unemployment insurance fraud. International Journal of Business Ecosystem & Strategy (2687-2293), 6(4), 253-270.

Rasul, I., Akter, T., Akter, S., Eshra, S. A., & Hossain, A. (2025). AI-Driven Business Analytics for Product Development: A Survey of Techniques and Outcomes in the Tech Industry. Frontline Marketing, Management and Economics Journal, 5(01), 16-38.

Sachin Dixit, & Jagdish Jangid. (2024). Asynchronous SCIM Profile for Security Event Tokens. Journal of Computational Analysis and Applications (JoCAAA), 33(06), 1357–1371. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/1935

Sawyer, S., Ellers, S., Kakumanu, M. S., Bommireddy, B., Pasgar, M., Susan-Kurian, D., ... & Jurdi, A. A. (2025). Trial in progress for a colorectal cancer detection blood test. https://ascopubs.org/doi/10.1200/JCO.2025.43.4_suppl.TPS306

Shabbir, A., Arshad, N., Rahman, S., Sayem, M. A., & Chowdhury, F. (2024). Analyzing surveillance videos in real-time using AI-powered deep learning techniques. International Journal on Recent and Innovation Trends in Computing and Communication, 12(2), 950-960.

Singh, D, & Gautam, A. (2024). Unlocking the Power of Big Data in Insurance: The Role of Data Analytics. In Data Alchemy in the Insurance Industry: The Transformative Power of Big Data Analytics (pp. 13-26). Emerald Publishing Limited.

Srirangam, R. K, Chennuri, S, & Pendyala, V. (2024). Technological disruption in P&C insurance: The impact of advanced analytics on risk assessment and customer engagement. International Journal of Research in Computer Applications and Information Technology (IJRCAIT), 7(2), 1224-1237.

Taneja, S, Bisht, V, & Kukreti, M. (2024). Revolutionizing Insurance Practices Through Advanced Data Alchemy. In Data Alchemy in the Insurance Industry: The Transformative Power of Big Data Analytics (pp. 119-131). Emerald Publishing Limited.

Tumai, W. J. (2021). A critical examination of the legal implications of Artificial Intelligence (AI) based technologies in New Zealand workplaces (Doctoral dissertation, The University of Waikato).

Umar, J, & Reuben, J. (2025). Fair AI in Real Estate and Insurance: Overcoming Bias and Improving Transparency in Machine Learning Models.

Vandervorst, F, Verbeke, W, & Verdonck, T. (2022). Data misrepresentation detection for insurance underwriting fraud prevention. Decision Support Systems, 159, 113798.

Yadav, S, & Bank, S. V. OPTIMIZING LIFE INSURANCE RISK ASSESSMENT THROUGH MACHINE LEARNING A DATA-DRIVEN APPROACH TO PREDICTIVE UNDERWRITING.

Zarifis, A, & Cheng, X. (2021, July). Evaluating the new AI and data driven insurance business models for incumbents and disruptors: Is there convergence?. In Business Information Systems (pp. 199-208).

Zaurez Afshar, M., & Hussain Shah, M. (2025). Performance Evaluation Using Balanced Scorecard Framework: Insights from A Public Sector Case Study. INTERNATIONAL JOURNAL OF HUMAN AND SOCIETY, 5(01), 40–47. https://ijhs.com.pk/index.php/IJHS/article/view/808