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Business Analytics and Large Language Models as Drivers of Operational Efficiency in Insurance: Stakeholder Evidence from NFP and Opteamix

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Abstract: Business analytics (BA) and large language models (LLMs) are increasingly embedded in underwriting, claims, fraud detection, compliance, and customer service, but their operational value depends on organizational readiness and responsible governance. This study examines stakeholder perceptions of how BA and LLMs affect operational efficiency in insurance, with contextual reference to NFP and its technology partner Opteamix. A cross-sectional survey of 120 purposively selected employees, managers, insurance professionals, customers, and subject-matter specialists was analysed using descriptive statistics, qualitative coding, correlation inspection, cross-tabulation, and a chi-square test. Respondents expressed strong agreement that BA and LLMs are critical to insurers' long-term success ($M = 3.98$), improve customer engagement ($M = 3.95$), strengthen fraud detection ($M = 3.92$), and accelerate claims processing ($M = 3.90$). Perceptions were less favorable for legacy-system integration ($M = 3.38$), privacy and security barriers ($M = 3.40$), skill shortages ($M = 3.40$), and implementation cost ($M = 3.50$). Open-ended responses produced 114 opportunity mentions and 62 challenge mentions, indicating qualified optimism. Perceptions of claims-efficiency improvement did not differ significantly across respondent roles, chi-square (12) = 11.97, $p = .448$, Cramer's $V = .18$. The findings suggest that BA offers relatively mature decision support, whereas LLM value remains conditional on workflow design, validation, data governance, human oversight, and workforce capability. A phased adoption framework is proposed that moves from bounded pilots to governed scaling, process integration, and continuous assurance.

Keywords: business analytics, large language models, insurance, operational efficiency, claims processing, underwriting, AI governance.

1. Introduction

Insurance is an information-intensive industry in which underwriting, pricing, claims adjudication, fraud control, and customer service depend on timely interpretation of structured and unstructured data. Traditional actuarial and rules-based systems remain essential, but insurers now face rising data volumes, customer expectations for faster service, increasingly complex fraud patterns, and closer regulatory scrutiny. These pressures create a strong business case for business analytics and generative artificial intelligence.

BA converts policy, claim, customer, financial, and operational data into descriptive, predictive, and prescriptive insight. It can improve risk segmentation, claim triage, fraud detection, portfolio monitoring, and managerial decision-making. LLMs extend this capability to natural-language tasks: extracting information from policy documents and adjuster notes, summarizing correspondence, supporting agents, drafting routine documents, and enabling conversational service. Their combination potentially reduces cycle time and manual workload while improving the consistency and accessibility of information.

Operational gains cannot be assumed from technical capability alone. Insurance decisions have direct consumer consequences and are governed by duties of accuracy, fairness, privacy, transparency, and regulatory compliance. The National Association of Insurance Commissioners *(NAIC, 2023)* therefore expects insurers using AI-supported decisions to maintain written governance, risk-management, validation, and documentation arrangements. The NIST AI Risk Management Framework likewise emphasizes lifecycle governance through the functions of govern, map, measure, and manage *(Tabassi, 2023)*, while its generative-AI profile highlights risks distinctive to foundation models, including confabulation, data privacy, information integrity, and human-AI configuration *(Autio et al., 2024)*.

Existing research shows that AI can contribute across the insurance value chain, including underwriting, claims, marketing, and after-sales service, but also raises robustness, adversarial, explainability, and governance concerns (*Aleksandrova et al., 2023; Amerirad et al., 2023; Owens et al., 2022)*. Predictive and AI-enabled operations in other service and enterprise contexts similarly show that technology creates organizational value when combined with reliable processes, user satisfaction, and operational capability (Jak*ata et al., 2025; Kishore et al., 2025; Nagaraju et al., 2024)*. What remains less clear is how stakeholders evaluate the relative benefits and implementation constraints of BA and LLMs in live insurance transformation settings.

This study responds to that gap through a stakeholder survey conducted in the context of NFP, a U.S.-based insurance broker and consultant, and Opteamix, a technology-services partner. It addresses three questions: Which operational outcomes are most strongly associated with BA and LLM adoption? Which organizational constraints are most salient? Do perceptions of claims-efficiency improvement differ across respondent roles? The article contributes a balanced post-adoption perspective that treats efficiency and governance as interdependent.

2. Literature Review and Conceptual Development

2.1. Business analytics and the insurance value chain

Analytics supports the conversion of historical and real-time data into decisions at multiple stages of the insurance value chain. In underwriting, predictive models can identify non-obvious risk patterns and improve consistency; in claims, classification and anomaly detection can prioritize cases and flag exceptions; in fraud control, machine-learning systems can identify suspicious combinations that rule-based procedures may miss. Evidence from insurance-fraud research shows substantial predictive potential, while also warning that performance depends on data quality, class imbalance, model design, and generalizability (Abakarim et al., 2023; Nabrawi & Alanazi, 2023).

Operational efficiency is multidimensional. It encompasses lower processing time and error rates, improved decision consistency, greater throughput, better resource utilization, and higher customer responsiveness. AI-driven supply-chain research likewise frames analytics as an operational coordination capability rather than a stand-alone tool (Nagaraju et al., 2024). Within insurance, the value of BA should therefore be assessed through workflow outcomes such as claim turnaround, underwriting accuracy, and fraud-screening reliability.

2.2. LLMs and language-intensive insurance work

Insurance operations contain large volumes of natural language: proposal forms, policy clauses, claim narratives, medical or legal documents, emails, call transcripts, and regulatory materials. LLMs can summarize, classify, retrieve, and generate text, thereby supporting employees in documentation-heavy workflows. Process-aware LLM research suggests that language models become more useful when grounded in explicit business-process context rather than deployed as generic conversational systems (Bernardi et al., 2024).

However, fluent output is not equivalent to factual reliability. LLMs may generate unsupported statements, reproduce sensitive information, inherit bias, or provide inconsistent answers. In high-stakes insurance decisions, unverified output could affect coverage, pricing, claim outcomes, or customer rights. Thus, LLMs are better treated as supervised decision-support systems with retrieval grounding, access controls, validation, audit logs, and human approval for consequential actions.

2.3. Organizational readiness and technology assimilation

Technology adoption becomes operationally meaningful only when it is assimilated into routines, roles, controls, and performance systems. Enterprise-system evidence indicates that user satisfaction mediates how implementation contributes to organizational performance (Kishore et al., 2025). Cross-sector predictive-maintenance research also illustrates that data models require stable workflows and clear operational ownership to create value (Jakata et al., 2025). For insurers, readiness therefore includes data quality, integration architecture, staff capability, leadership support, regulatory knowledge, and change acceptance.

2.4. Responsible AI and insurance governance

Responsible adoption requires more than a general ethics statement. Insurers must define acceptable uses, ownership, validation thresholds, escalation routes, model monitoring, third-party controls, and evidence for regulatory examination. Explainability is particularly important in underwriting and claims because affected customers and regulators may require understandable reasons for decisions *(Owens et al., 2022)*. The NAIC model bulletin reinforces this outcome-based expectation by linking AI governance to existing insurance law and unfair-trade-practice obligations *(NAIC, 2023)*.

Based on the literature and the exploratory character of the study, four propositions guide the analysis: BA and LLMs are perceived to improve core insurance operations; they are perceived to enhance customer-facing performance; implementation constraints temper their benefits; and perceptions of claims-efficiency improvement may vary across organizational roles.

3. Materials and Methods

3.1. Design and context

The study used a descriptive, cross-sectional mixed-method design. The empirical setting combined perspectives connected with NFP insurance operations and Opteamix technology projects. Quantitative items measured perceptions of BA and LLM awareness, use, operational outcomes, barriers, and future readiness. Open-ended responses provided contextual explanations and were coded into opportunity and challenge themes.

3.2. Sampling and participants

Purposive sampling was used to recruit 120 participants with relevant exposure to insurance, analytics, digital transformation, or customer experience. The sample included entry-level employees, mid-level managers, senior managers or executives, consultants or subject-matter experts, NFP-related professionals, Opteamix employees, and selected insurance customers. Most respondents were mid-career professionals with three to ten years of experience; senior leadership was less represented. Because selection probabilities were unavailable, the results are exploratory and should not be generalized as industry prevalence estimates.

3.3. Instrument and measures

The questionnaire included demographic questions and 17 perception statements (Q5-Q21), each measured on a five-point agreement scale from 1 (strongly disagree) to 5 (strongly agree). Items covered awareness, organizational investment, training, underwriting accuracy, workload automation, claims efficiency, fraud detection, customer engagement, personalization, customer-service speed, legacy integration, privacy, cost, skill availability, strategic importance, and adoption readiness. Open-ended items invited respondents to identify opportunities and challenges.

3.4. Analysis

Item means were used to summarize the perception profile. The source study inspected inter-item correlations and reported strong positive relationships above .70 among several benefit items, but did not retain the complete coefficient matrix; therefore, this paper does not reproduce unverified coefficients. Open-ended comments were coded by keyword theme and aggregated as opportunity or challenge mentions. A cross-tabulation and Pearson chi-square test assessed whether responses to Q11 (analytics improves claims speed and efficiency) differed across four respondent-role categories. Cramer's V was calculated from the reported chi-square statistic as an effect-size supplement. Statistical significance was evaluated at alpha = .05.

4. Results

4.1. Perceived benefits and readiness

The overall profile was favorable. Long-term strategic importance and future readiness each received a mean of 3.98. Customer engagement (M = 3.95), organizational training (M = 3.96), technology investment (M = 3.92), fraud detection (M = 3.92), claims efficiency (M = 3.90), and underwriting accuracy (M = 3.88) were also rated positively. LLM-enabled workload automation received a comparatively moderate score (M = 3.64), suggesting that expectations may be ahead of consistent workflow-level realization.

Table 1: Highest-rated benefit and readiness items

Item	Construct	Mean
Q20	BA/LLMs are critical to long-term success	3.98
Q21	Organization is prepared for future adoption	3.98
Q8	Training and awareness programmes	3.96
Q13	Customer engagement and satisfaction	3.95
Q7	Organizational investment in BA/AI	3.92
Q12	Reliability of fraud detection	3.92
Q11	Claims speed and efficiency	3.90
Q9	Underwriting and risk accuracy	3.88

Note. Five-point scale: 1 = strongly disagree, 5 = strongly agree; N = 120.

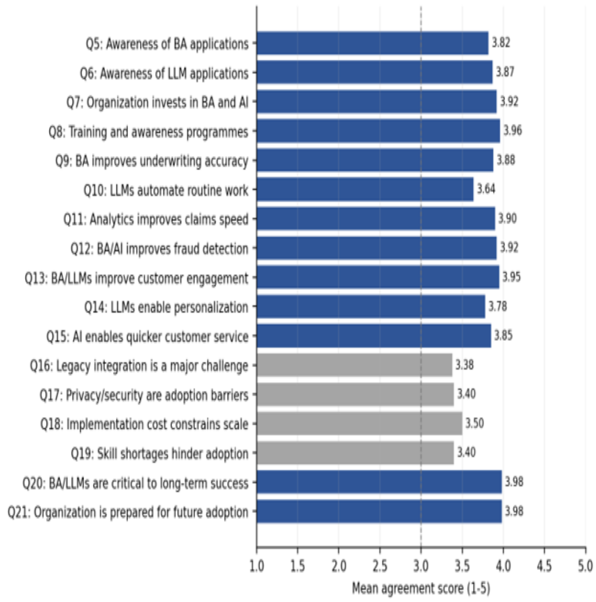

Figure 1: Mean perception profile for BA and LLM adoption

4.2. Implementation constraints

Respondents acknowledged important adoption barriers, although the means remained closer to neutral than to strong agreement. Legacy-system integration had the lowest mean (M = 3.38), followed by privacy and security (M = 3.40), skill shortages (M = 3.40), and implementation cost (M = 3.50). These values should not be interpreted as absence of risk. Instead, they indicate heterogeneous experience: some respondents faced material constraints while others worked in settings with stronger capabilities or fewer implementation difficulties.

Table 2: Implementation-barrier profile

Item	Barrier	Mean	Interpretation
Q16	Legacy-system integration	3.38	Moderate/divided
Q17	Data privacy and security	3.40	Moderate concern
Q19	Shortage of skilled professionals	3.40	Moderate concern
Q18	High implementation cost	3.50	Moderate concern
Q10	LLM automation of routine workload	3.64	Benefit not yet uniform

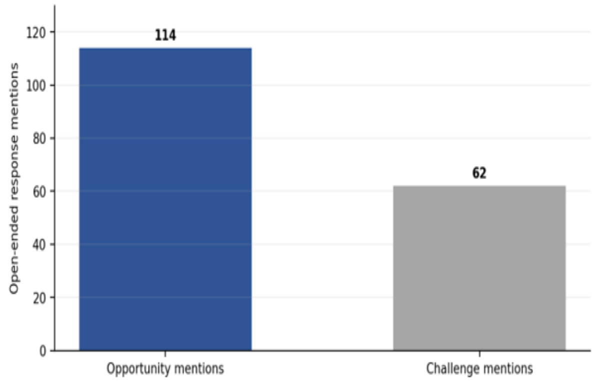

Figure 2: Opportunity and challenge mentions in open-ended responses

4.3. Opportunity-challenge coding

The open-ended responses yielded 114 opportunity mentions and 62 challenge mentions, a ratio of 1.84 to 1. Opportunity themes emphasized automation, faster processing, improved customer experience, fraud reduction, predictive decision support, and potential return on investment. Challenge themes emphasized data quality, privacy, regulatory uncertainty, integration, cost, and training. The imbalance indicates qualified optimism rather than uncritical acceptance.

4.4. Respondent role and perceived claims efficiency

The chi-square test was not statistically significant, chi-square $(12, N = 120) = 11.97$, $p = .448$. The derived effect size was small, Cramer's $V = .18$. Thus, the sample does not provide evidence that perceptions of claims-efficiency improvement differ systematically across respondent roles.

Table 3: Cross-tabulation of role by Q11 response

Role	Agree	Neutral	Strongly agree	Disagree	Strongly disagree	Total
Consultant/SME	5	1	3	0	0	9
Entry-level employee	19	8	8	5	3	43
Mid-level manager	22	5	16	1	0	44
Senior manager/executive	13	4	5	1	1	24
Total	59	18	32	7	4	120

Table 4: Inferential test summary

Test	Statistic	df	p	Effect size	Decision
Role x claims-efficiency perception	11.97	12	.448	Cramer's V = .18	No significant association

5. Discussion

5.1. Analytics as the mature efficiency layer

Respondents associated BA most clearly with underwriting accuracy, claims speed, and fraud-detection reliability. These are functions where structured historical data, established performance metrics, and measurable process outcomes make analytics comparatively mature. The findings align with prior evidence that predictive models can improve claim forecasting and fraud screening *(Abakarim et al., 2023; Jaiswal et al., 2024; Nabrawi & Alanazi, 2023).* Operational value arises not merely from model accuracy, but from how predictions are embedded in triage, escalation, and review workflows.

5.2. LLM value is conditional on workflow grounding

The relatively lower score for LLM-enabled workload automation suggests a maturity gap between awareness and routinized value. LLMs can summarize documents and support service interactions, but generic deployment may create unreliable or untraceable output. Process-aware grounding, authoritative retrieval sources, constrained prompts, and human approval can make language-model assistance more dependable *(Bernardi et al., 2024).* Insurers should therefore evaluate LLMs through task-level measures such as correction rate, time saved, unsupported-claim frequency, escalation quality, and customer outcome—not demonstrations of fluency.

5.3. A shared operational view across roles

The nonsignificant role-by-Q11 test indicates broad agreement that analytics improves claims efficiency. This is strategically useful because transformation often fails when technical, managerial, and operational groups hold conflicting value assumptions. However, the result should not be overextended: sparse cells and purposive sampling limit inference, and role agreement on benefits does not guarantee agreement on implementation priorities or acceptable risk.

5.4. Governance and readiness as value-enabling capabilities

The barrier profile shows that integration, privacy, skills, and cost remain material even when overall sentiment is positive. These are not external obstacles to be addressed after deployment; they determine whether deployment creates sustainable value. The findings reinforce the NAIC's emphasis on an insurer-wide AI systems programme and the NIST emphasis on governance across the lifecycle *(Autio et al., 2024; NAIC, 2023; Tabassi, 2023)*. They also echo enterprise-system research in which user satisfaction and organizational performance depend on implementation quality and human adoption *(Kishore et al., 2025)*.

5.5. Theoretical contribution

The study contributes an assimilation perspective to insurance AI research. BA and LLMs are not interchangeable technologies: BA is perceived as a more established decision layer, while LLMs are an emerging language-work layer whose value depends on grounding and oversight. Operational efficiency is therefore produced through a configuration of analytical capability, process integration, workforce competence, and governance. The opportunity-to-challenge ratio further demonstrates that positive expectations coexist with implementation realism.

6. Practical and Policy Implications

6.1. A phased adoption framework

Insurers should begin with bounded, reversible use cases such as internal document search, claim summarization for human review, quality assurance, and fraud-alert prioritization. Each pilot should have a process owner, approved data sources, baseline measures, validation criteria, human override, incident reporting, and a defined exit condition. Successful pilots can then be scaled across functions only after security, privacy, fairness, and operational performance are demonstrated.

Table 5: Governed adoption roadmap

Stage	Priority use	Required controls	Evidence for progression
Pilot	Low-consequence assistance and retrieval	Approved data, access control, human review, baseline metrics	Accuracy, correction rate, time saved, incident log
Scale	Claims triage, fraud alerts, service support	Model inventory, validation, role training, vendor controls	Stable performance across teams and customer groups
Integrate	Workflow and legacy-system embedding	APIs, audit trails, exception routing, change control	Reduced cycle time and errors without adverse outcomes
Assure	Continuous governed operation	Drift monitoring, fairness review, security testing, regulatory evidence	Sustained benefits, explainability, timely remediation
Innovate	Insurance-specific models and advanced decision support	Board oversight, independent challenge, controlled experimentation	Documented business value and acceptable residual risk

Note. The roadmap synthesizes the survey findings with NAIC and NIST governance expectations.

6.2. Managerial implications

NFP and Opteamix should establish joint ownership across business, data, technology, legal, compliance, security, and operations. Training should be role-specific: users need verification and escalation skills; managers need model-performance and risk interpretation; developers need secure design and evaluation practices; compliance teams need access to logs, documentation, and testing evidence. Technology investment should be accompanied by process redesign so that automation does not merely accelerate inefficient workflows.

6.3. Regulatory and consumer implications

Where AI supports consequential decisions, insurers should preserve understandable reasons, human appeal routes, and evidence that outcomes comply with applicable insurance law. Third-party models require contractual access to documentation, testing results, incident notification, data provenance, and change information. Customer-facing LLMs should disclose their automated nature, avoid making unauthorized coverage commitments, and escalate ambiguous or high-impact questions to qualified staff.

7. Limitations and Future Scope

The study is limited by purposive sampling, a modest sample size, mixed respondent categories, and concentration on NFP- and Opteamix-related contexts. The design is cross-sectional and perception-based, so it cannot establish causal efficiency gains. Objective indicators such as claim turnaround, error rates, fraud recoveries, complaint levels, or cost-to-serve were unavailable. The instrument used single statements rather than validated multi-item constructs, and reliability or factor analysis was not reported. The complete correlation matrix and raw data were not available for verification. The chi-square table contains sparse cells, reducing confidence in asymptotic inference.

Future studies should use stratified samples and distinguish employees, managers, customers, and technical specialists. Longitudinal or quasi-experimental designs could compare operational metrics before and after deployment. Validated constructs should measure analytics capability, LLM usefulness, data governance, readiness, trust, and operational efficiency. Structural-equation models could test whether readiness and governance mediate or moderate technology-performance relationships. Audit-based studies should also examine accuracy, bias, explainability, privacy leakage, and model drift in actual underwriting, claims, and service workflows.

8. Conclusions

Stakeholders view business analytics and LLMs as important drivers of insurance transformation, particularly through faster claims, stronger fraud detection, improved underwriting, and more responsive customer engagement. Yet the evidence also reveals an assimilation gap: technical optimism is stronger than confidence in integration, privacy, cost, and skills. BA appears to be the more mature operational capability, while LLMs require careful task definition, grounding, validation, and human oversight. For NFP, Opteamix, and comparable insurers, the strategic priority is not rapid deployment in isolation, but governed integration that produces measurable efficiency without compromising fairness, security, accuracy, or accountability.

References

1. Abakarim, Y., Lahby, M., & Attioui, A. (2023). A bagged ensemble convolutional neural networks approach to recognize insurance claim frauds. Applied System Innovation, 6(1), Article 20. https://doi.org/10.3390/asi6010020
2. Aleksandrova, A., Ninova, V., & Zhelev, Z. (2023). A survey on AI implementation in finance, (cyber) insurance and financial controlling. Risks, 11(5), Article 91. https://doi.org/10.3390/risks11050091
3. Amerirad, B., Cattaneo, M., Kenett, R. S., & Luciano, E. (2023). Adversarial artificial intelligence in insurance: From an example to some potential remedies. Risks, 11(1), Article 20. https://doi.org/10.3390/risks11010020
4. Autio, C., Schwartz, R., Dunietz, J., Jain, S., Stanley, M., Tabassi, E., Hall, P., & Roberts, K. (2024). Artificial intelligence risk management framework: Generative artificial intelligence profile (NIST AI 600-1). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.600-1
5. Bernardi, M. L., Casciani, A., Cimitile, M., & Marrella, A. (2024). Conversing with business process-aware large language models: The BPLLM framework. Journal of Intelligent Information Systems, 62, 1607–1629. https://doi.org/10.1007/s10844-024-00898-1
6. Huang, X., Ruan, W., Huang, W., Jin, G., Dong, Y., Wu, C., Bensalem, S., & Mu, R. (2024). A survey of safety and trustworthiness of large language models through the lens of verification and validation. Artificial Intelligence Review, 57, Article 175. https://doi.org/10.1007/s10462-024-10824-0
7. Jaiswal, R., Gupta, S., & Tiwari, A. K. (2024). Big data and machine learning-based decision support system to reshape the vaticination of insurance claims. Technological Forecasting and Social Change, 209, Article 123829. https://doi.org/10.1016/j.techfore.2024.123829
8. Jakata, M. S., Ellaturu, N., Sahana, V., Yashaswini, M., Dileep, S., & Bhoomika, R. (2025). Deep learning-driven predictive maintenance framework for smart hospital operations. In 2025 Tenth International Conference on Science Technology Engineering and Mathematics. IEEE.
9. Kishore, P. V. K., Vemaraju, S., Ellaturu, N., & Kumari, T. L. (2025). Implementation of Enterprise Resource Planning (ERP) system in manufacturing companies: Effect on user satisfaction and organizational performance. International Journal of Experimental Research and Review, 48, 42–50. https://doi.org/10.52756/ijerr.2025.v48.005
10. Nabrawi, E., & Alanazi, A. (2023). Fraud detection in healthcare insurance claims using machine learning. Risks, 11(9), Article 160. https://doi.org/10.3390/risks11090160
11. Nagaraju, E., Kumari, T. L., Bambuwala, S., & Rajalakshmi, M. (2024). AI-driven solutions for supply chain management. Journal of Informatics Education and Research, 4(2).
12. National Association of Insurance Commissioners. (2023, December 4). NAIC members approve model bulletin on use of AI by insurers. https://content.naic.org/article/naic-members-approve-model-bulletin-use-ai-insurers
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. Tabassi, E. (2023). Artificial intelligence risk management framework (AI RMF 1.0) (NIST AI 100-1). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.100-1