Multidisciplinary Reviews

REVIEW ARTICLE
Published Online: April 14, 2025
https://doi.org/10.31893/multirev.2025323

Sentiment analysis in insurance: A systematic review of approaches, techniques, and applications

Luqman Hakim[a] ✉ | **Ilyas Nuryasin**[a] | **Suryanto Nugroho**[b]

[a]Faculty of Engineering, Department of Informatics, Universitas Muhammadiyah Malang, East Java, Indonesia.
[b]Faculty of Science and Technology, Department of Informatics, ITS PKU Muhammadiyah Surakarta, Kota Surakarta, Central Java, Indonesia.

Abstract The increasing reliance on sentiment analysis within the insurance industry highlights the growing importance of accurately interpreting customer feedback to inform strategic decisions, enhance customer engagement manage risks. However, the dynamic and ever-changing nature of online language poses a to the long-term effectiveness of sentiment analysis models. These models often degrade in accuracy over time because of their inability to adapt to new linguistic patterns, emerging terminology shifts in consumer expression driven by external events, regulatory developments competitive pressures. This study investigates the critical necessity for the continuous adaptation and retraining of sentiment analysis models to maintain relevance and accuracy in the insurance sector. Through a qualitative approach, the research examines key drivers of language evolution, including social discourse, cultural trends institutional changes. It also explores the implications of outdated sentiment models on business performance, particularly regarding misinterpreting customer sentiment, delayed response to market signals, and reduced risk mitigation capabilities. The findings suggest that continuous retraining mechanisms significantly enhance model performance, improving sentiment classification, deeper customer insights, and more responsive decision-making processes. In addition, adaptive sentiment analysis enables insurers to proactively identify reputational and operational risks, ultimately improving organizational efficiency and resilience. This study concludes that ongoing model adaptation should be a strategic priority for insurance firms seeking to harness the full potential of digital sentiment data. It recommends further research into developing robust, context-aware natural language processing (NLP) models, ethical considerations of automated sentiment monitoring, and tailored application of these systems across various insurance products and services.

Keywords: sentiment analysis, natural language processing, insurance, online discourse, continuous learning

1. Introduction

Sentiment analysis, or opinion mining, is crucial for understanding public attitudes, especially during significant events such as the COVID-19 pandemic. Studies have demonstrated that sentiment analysis can effectively gauge emotional responses in various contexts, such as health behaviors influenced by online communities (Chen, 2023) and the communication strategies of legislators on social media (Guntuku et al., 2021; Sharma & Jain, 2020). For example, Guntuku et al. highlighted how sentiment analysis of the Twitter language among U.S. legislators provided insights into public health messaging during the pandemic (Guntuku et al., 2021). Furthermore, Kusuma's research on long-term COVID-19 sentiment on Twitter revealed prevalent negative emotions linked to ongoing health challenges, underscoring the emotional toll of the pandemic (Kusuma & Suherman, 2024). Machine learning techniques, such as support vector machines, have demonstrated enhanced sentiment analysis accuracy across different applications, including health care (Hokijuliandy et al., 2023; Qahar et al., 2024). This multifaceted approach to sentiment analysis not only aids in understanding public opinion but also informs policy and health care responses during crises (Kastrati et al., 2023).

Sentiment analysis can be conducted at various levels of granularity, including the document, sentence, and aspect levels (Aditya, 2024). Document-level sentiment analysis assesses the overall sentiment of an entire text, whereas sentence-level analysis focuses on individual sentences to capture nuanced emotions (Chen, 2023; Guntuku et al., 2021). Aspect-level sentiment analysis evaluates sentiments related to specific features or aspects of the text, allowing for a more detailed understanding of the opinions expressed (Kusuma & Suherman, 2024). For example, studies have utilized sentiment analysis to evaluate public health communication during the COVID-19 pandemic, revealing how different aspects of messaging influenced public perception and behavior (Guntuku et al., 2021). Additionally, machine learning techniques, such as support vector machines, have been effectively employed to increase the accuracy of sentiment classification across these various levels, demonstrating the versatility and applicability of sentiment analysis in diverse fields, including healthcare and social media (McCoy et al., 2015; Qahar et al., 2024).

 Received: February 6, 2025 | Accepted: March 11, 2025

Sentiment analysis employs various techniques, including lexicon-based, machine learning-based, and hybrid approaches that integrate both methods (Hayatin et al., 2020). Lexicon-based approaches utilize predefined lists of words and their associated sentiments to gauge a text's overall sentiment (Guntuku et al., 2021). In contrast, machine learning-based techniques leverage algorithms such as support vector machines (SVMs) and naïve Bayes to classify sentiments on the basis of training data, allowing for a more nuanced understanding and adaptability to different contexts (McCoy et al., 2015). Hybrid approaches combine these methods, to increase accuracy by using the strengths of both lexicon and machine learning techniques (Uncovska et al., 2023). For example, Nitiéma's study on telehealth opinions illustrates how machine learning can effectively analyze user sentiment while incorporating lexicon-based insights to improve classification performance (Nitiema, 2022). This multifaceted approach is particularly valuable in fields such as healthcare, where understanding public sentiment can inform policy and communication strategies (Zhou et al., 2021).

Sentiment analysis has various applications across various sectors, significantly impacting customer experience management, product feedback analysis, brand monitoring, social media analysis, and financial market prediction. In customer experience management, sentiment analysis helps businesses understand consumer opinions and improve service delivery (Chen, 2023; Chiarello et al., 2020). For example, Guntuku et al. demonstrated how social media sentiment analysis can inform public health messaging, which is crucial for brand monitoring and reputation management (Guntuku et al., 2021). Additionally, sentiment analysis is instrumental in analyzing product feedback, as seen in studies that leverage customer reviews to identify potential product defects and enhance quality control (Fong et al., 2021). In finance, sentiment analysis has been employed to predict market trends, with research indicating that public sentiment can significantly influence stock prices and investment decisions (Claus & Stella, 2022; Shang et al., 2022). Overall, integrating sentiment analysis into these applications enables organizations to make data-driven decisions and respond effectively to stakeholder needs.

The insurance industry has increasingly recognized the value of sentiment analysis to increase customer understanding, improve service delivery, and identify emerging market trends and risks. By analyzing customer sentiment expressed through various channels, insurers can tailor their offerings and communication strategies to meet clients' better needs (Claus & Stella, 2022). For example, while the study by Fong (Fong et al., 2021) focused on product recalls rather than general customer sentiment in insurance, it highlighted the importance of customer feedback in proactive decision-making. Furthermore, sentiment analysis can provide insights into market trends, helping insurers anticipate consumer behavior shifts and adjust their strategies accordingly (Shang et al., 2022). This approach is particularly relevant in public health events, where understanding investor sentiment can influence insurance companies' investment decisions and risk management strategies (Shang et al., 2022). Overall, integrating sentiment analysis into the insurance sector improves customer engagement and supports data-driven decision-making in an increasingly competitive market.

The specialized terminology and complex insurance policy language significantly significantly challenge standard sentiment analysis models. Research indicates that traditional sentiment analysis methods often struggle to accurately interpret nuanced insurance jargon, which can lead to misinterpretations of sentiment in customer feedback and policy documents (Claus & Stella, 2022). For instance, the lexicon-based sentiment analysis employed in the study by Claus and Stella revealed only a weak correlation between sentiment levels and financial indicators, highlighting the limitations of conventional approaches in capturing the intricacies of insurance language (Claus & Stella, 2022). Furthermore, while machine learning techniques, such as support vector machines (SVMs), have shown promise in improving sentiment classification, these methods still face obstacles when dealing with domain-specific language (Hokijuliandy et al., 2023). Consequently, the need for tailored sentiment analysis frameworks that can accommodate the unique linguistic characteristics of the insurance sector is evident, as existing models often fail to provide accurate insights into customer sent (Claus & Stella, 2022; Hokijuliandy et al., 2023).

Insurance sector sentiment is highly subjective and context dependent, which necessitates a nuanced analysis to gauge customer sentiment accurately. The complexity of insurance language and the emotional weight of financial decisions complicates sentiment analysis. For example, the study by Hokijuliandy highlighted the effectiveness of machine learning techniques, such as support vector machines (SVMs), in sentiment classification while acknowledging the challenges posed by domain-specific terminology ((Hokijuliandy et al., 2023). Furthermore, the qualitative study by Proost et al. emphasized how individual perceptions, particularly regarding reimbursement issues, can significantly influence sentiment, illustrating the need for context-aware analysis (De Proost et al., 2022). Additionally, Denkowska and Wanat's research on systemic risk in the insurance sector underscores the importance of understanding the emotional undercurrents in consumer sentiment, as market sentiment can directly impact systemic risk factors (Denkowska & Wanat, 2020). Thus, developing advanced sentiment analysis frameworks that incorporate contextual nuances is crucial for accurately interpreting customer sentiment in the insurance domain (De Proost et al., 2022; Denkowska & Wanat, 2020; Hokijuliandy et al., 2023).

The challenges associated with training effective sentiment analysis models in the insurance domain are exacerbated by the limited availability of publicly accessible datasets and the imbalanced sentiment distributions often found in real-world data. Research indicates that the scarcity of domain-specific datasets hinders the development of robust models that accurately interpret sentiment nuances within insurance contexts (Claus & Stella, 2022). For example, while Al-Garadi et al. discuss the potential of social media data for understanding complex emotional dynamics, their focus is not specifically on the insurance sector, limiting their findings' applicability to this domain (Al-Garadi et al., 2022). Furthermore, the imbalanced nature of sentiment distributions—where positive or negative sentiments may dominate—can lead to biased model training, as highlighted by Chen's exploration of sentiment analysis in health-related online communities, which may not directly correlate with insurance sentiment analysis (Chen, 2023). This imbalance can skew results, making it difficult for models to generalize effectively across diverse sentiment expressions (Hokijuliandy et al., 2023). Therefore, addressing these challenges requires innovative approaches to data collection and model training that specifically cater to the unique characteristics of the insurance industry (Claus & Stella, 2022).

The dynamic nature of the language used in online insurance discussions, including the emergence of new terms and slang, necessitates continuous updates and adaptations of sentiment analysis models to maintain accuracy (Minarno et al., 2021). As highlighted by Claus and Stella, the evolving lexicon of the insurance sector requires sentiment analysis frameworks to be regularly refined to effectively capture the nuances of emerging terminology (Claus & Stella, 2022). Moreover, , Denkowska and Wanat (2020) emphasized that sentiment analysis must account for contextual changes in language, particularly in response to market dynamics and consumer behavior (Denkowska & Wanat, 2020). The rapid evolution of language in digital discussions can lead to outdated models that fail to recognize new expressions or sentiments, as noted in research examining social media's role in shaping public opinions (Al-Garadi et al., 2022). Consequently, ongoing training and adaptation of sentiment analysis models are essential to ensure that they remain relevant and effective in interpreting the sentiments expressed in insurance-related conversations (Claus & Stella, 2022; Denkowska & Wanat, 2020; Qahar et al., 2024).

Integrating sentiment analysis tools into insurance workflows presents significant challenges related to data privacy, security, and regulation compliance. The sensitive nature of insurance data necessitates stringent adherence to privacy laws, such as the General Data Protection Regulation (GDPR) in Europe and various state-level regulations in the U.S. (Guntuku et al., 2021). This complexity is compounded by the need for robust security measures to protect customer information from breaches, as highlighted by the increasing prevalence of cyber threats in the digital landscape (Nitiema, 2022). Furthermore, compliance with industry standards and regulations adds another layer of complexity to the implementation process, requiring organizations to ensure that their sentiment analysis tools do not inadvertently violate legal requirements (Kusuma & Suherman, 2024). As noted by Denkowska and Wanat, integrating advanced analytical tools must be approached with caution, balancing the benefits of enhanced customer insights against the potential risks associated with data handling and regulatory compliance (Denkowska & Wanat, 2020). Thus, a comprehensive strategy that addresses these concerns is essential for successful implementation (Chen, 2023; Kusuma & Suherman, 2024; Nitiema, 2022)

While the challenges of sentiment analysis in insurance are substantial, some argue that current tools and techniques offer sufficient value. General-purpose sentiment analysis models, while imperfect, can identify broad trends in customer feedback, providing a proper high-level view of sentiment. They argue that the emphasis on domain-specific language is overstated because many customer sentiments are expressed using common language that is easily understood using general models. The increasing availability of pretrained models and labeled datasets further reduces the need for extensive custom development. For smaller insurance companies with limited resources, the benefits of readily available sentiment analysis tools may outweigh the costs and complexities of building specialized solutions.

Advances in natural language processing advancements are constantly improving the accuracy and adaptability of sentiment analysis models. Techniques such as transfer learning allow models trained on large general datasets to be fine-tuned for specific domains, such as insurance, by leveraging existing knowledge while adapting to specialized language. The development of contextualized word embeddings, which capture the meaning of words on the basis of their surrounding context, also helps address the challenges of ambiguity and nuanced language. As NLP technology evolves, the gap between general-purpose and domain-specific sentiment analysis will likely narrow, which will make readily available tools even more effective for insurance applications.

Finally, some argue that a pragmatic approach to sentiment analysis in insurance involves combining automated tools with human review and interpretation. While automated analysis can quickly process large volumes of data, human analysts can provide valuable context and insights, especially when dealing with complex or ambiguous cases. This hybrid approach leverages the strengths of automated and human analysis, providing a more comprehensive and nuanced understanding of customer sentiment. Despite their current limitations, insurance companies can derive significant value from sentiment analysis by focusing on practical applications and combining technology with human expertise.

This study is important because it was motivated by the significant gap between the potential of sentiment analysis and its practical application in the insurance industry. Although sentiment analysis holds promise for enhancing various aspects of the insurance business, from customer assessment to risk assessment, several challenges hinder its effective implementation. These challenges form the core rationale for this research. Specifically, the complex and specialized language of insurance, the scarcity of relevant training data, and the need to integrate sentiment analysis tools into existing workflows while adhering to strict data privacy and security regulations pose significant obstacles. This study delves into these challenges and explores the technical limitations and practical considerations that must be addressed to fully realize the benefits of sentiment analysis in the insurance sector.

This study aims to comprehensively investigate the challenges and opportunities of sentiment analysis in the insurance industry. This study explores the limitations of current sentiment analysis techniques when applied to the complex and nuanced language of insurance communication. This study also examines the impact of data scarcity and imbalance on the effectiveness of sentiment analysis models in this domain. Finally, this study analyzes the need for continuous adaptation and retraining of models to keep pace with the evolving language used in online insurance discussions. By addressing these key areas, this study contributes to contribute to the development of more effective and tailored sentiment analysis solutions for the insurance sector. The journal *Information Technology and Control* gives preference to manuscripts of high scientific level, which have not been published and are written not only for specialists but also for the general public interested in the questions of computer science and control systems.

2. Methods

This research employed a systematic literature review methodology to analyze existing knowledge on sentiment analysis within the insurance industry. The Scopus database was chosen as the primary source for this review because of its comprehensive coverage of scholarly literature. The initial search used utilized the keywords "sentiment," "analysis," and "insurance," yielding 165 documents. To focus on the most relevant and contemporary research, the timeframe was restricted to the past 15 years (2010-2025), resulting in 159 documents.

Further refinement involved limiting the subject area to a broad range of disciplines relevant to the study, including Computer Science, Engineering, Medicine, Mathematics, Business, Management and Accounting, Decision Sciences, Social Sciences, Economics, Econometrics and Finance, Physics and Astronomy, Multidisciplinary, Pharmacology, Toxicology and Pharmaceutics, Materials Science, Energy, Nursing, Health Professions, and Environmental Science. This subject area filter reduced thenumber of documents to 155. To ensure the inclusion of high-quality peer-reviewed research, the search was limited to article types, resulting in 77 articles. A thorough screening of the abstracts of these articles was conducted to assess their relevance to the research questions, further narrowing the pool to 45 articles. Finally, a full-text review of the remaining articles was performed, resulting in a final set of 27 articles that formed the basis for the analysis and discussion presented in this study. This rigorous selection process ensured the inclusion of the most relevant and high-quality research on sentiment analysis in the insurance industry.

The 27 articles selected for this review represent research conducted across various countries, reflecting global interest in sentiment analysis within the insurance sector. Specifically, studies from Switzerland, South Africa, the United States, Indonesia, Poland, China, Belgium, Thailand, the United Kingdom, Finland, Germany, and India comprised a significant portion of the reviewed literature, indicating a concentration of research activity in these regions. Although these countries contributed the most publications, the review also included studies from other countries, providing a diverse perspective on the challenges and opportunities associated with applying sentiment analysis in the insurance industry across different national contexts.

3. Results and Discussion

3.1. Investigate the challenges and opportunities of sentiment analysis in the insurance industry

Applying sentiment analysis in insurance industry presents significant challenges and promising opportunities. Understanding these dynamics is crucial as the industry increasingly seeks to leverage customer feedback and market sentiment to enhance service delivery and product offerings.

Complex Terminology and Contextual Nuances: The insurance sector is characterized by specialized terminology and complex policy language, which can lead to difficulty in accurately interpreting sentiment. Traditional sentiment analysis models often struggle with the nuanced meanings of terms that may have different implications in various contexts. For instance, Proost et al. highlighted how qualitative insights into consumer sentiment are often overshadowed by the complexity of the language used in specific contexts, such as reimbursement discussions in healthcare (De Proost et al., 2022). This complexity necessitates the development of sophisticated models that can adapt to the unique linguistic features of the insurance domain.

Data Privacy and Compliance Issues: Integrating sentiment analysis tools into insurance workflows requires careful consideration of data privacy and compliance regulations. The sensitive nature of insurance data means that organizations must navigate a complex landscape of regulations, such as the GDPR in Europe and the HIPAA in the United States, which govern the handling of personal information (Chen, 2023). Ensuring compliance while leveraging customer data for sentiment analysis adds a layer of complexity to implementation processes because organizations must balance the need for insights with the imperative to protect consumer privacy.

Limited availability of domain-specific datasets: The scarcity of publicly available datasets specific to the insurance industry poses a significant challenge to training effective sentiment analysis models. Many existing datasets are not tailored to the unique language and sentiment expressions found in insurance discussions, which can lead to biased or inaccurate model outputs (Guntuku et al., 2021). Hokijuliandy's research highlights the predominance of positive sentiments in user reviews for health insurance applications, indicating an imbalance that can skew model training and lead to biased outcomes (Hokijuliandy et al., 2023). In addition, imbalanced sentiment distributions in real-world data can skew results, which makes it difficult for models to generalize across diverse sentiment expressions. This limitation underscores the need to develop robust, domain-specific datasets to increase the accuracy of sentiment analysis in insurance.

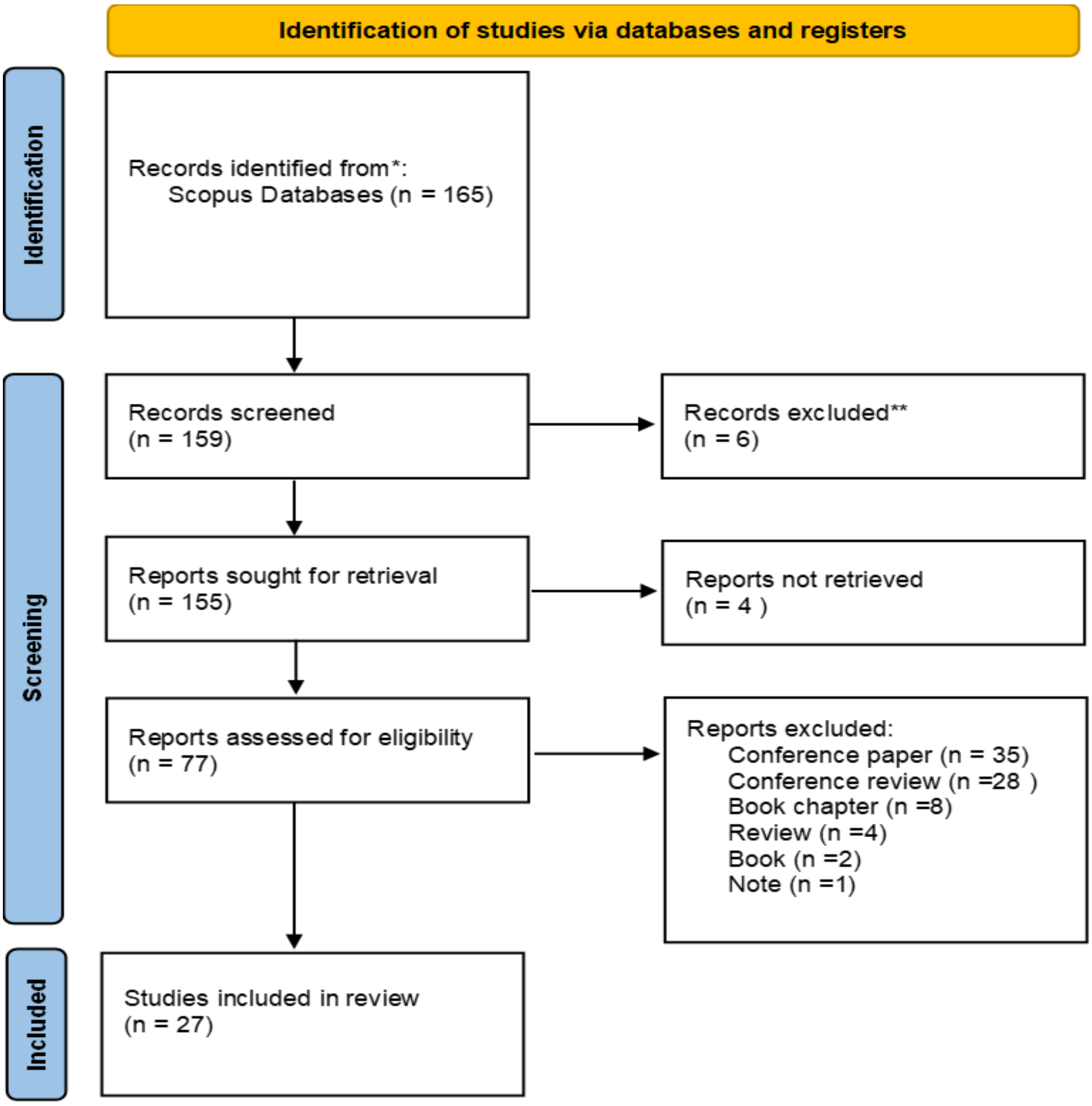

Figure 1 PRISMA flowchart of the identification and selection of studies.

Rapidly Evolving Language and Trends: The language used in online discussions about insurance is constantly evolving, with new terms and slang regularly emerging. This dynamic nature of language requires continuous updates and adaptations of sentiment analysis models to maintain accuracy (Fong et al., 2021). While Denkowska and Wanat discussed systemic risk in the insurance sector, their findings did not directly address the integration of advanced analytical tools in sentiment analysis, indicating a gap in the literature regarding the specific challenges posed by evolving language in this context (Denkowska & Wanat, 2020). As consumer preferences and market conditions change, sentiment analysis tools must be agile enough to incorporate new linguistic trends and sentiment expressions to remain relevant and practical.

Integration with Existing Workflows: Successfully integrating sentiment analysis tools into insurance workflows requires careful planning and execution. Organizations must consider how these tools interact with current systems and processes to ensure that they enhance rather than disrupt operations. The need for cross-departmental collaboration compounds this integration challenge, as insights derived from sentiment analysis must be effectively communicated and acted upon across various teams within the organization (Denkowska & Wanat, 2020).This integration process often requires significant investments in technology and training, which can hinder implementation (Claus & Stella, 2022).

3.1.1. Opportunities for applying sentiment analysis in insurance

Enhanced Customer Insights: Despite these challenges, sentiment analysis offers significant opportunities for gain deeper insights into customer preferences and experiences. Insurance companies can identify trends and sentiments that inform product development and service improvements by analyzing customer feedback. For example, Hokijuliandy's study on the sentiment analysis of user reviews for a national health insurance application demonstrated the potential for extracting valuable insights that can enhance user experience and satisfaction (Hokijuliandy et al., 2023). These insights can lead to more tailored offerings that resonate with customers.

Proactive risk management: Sentiment analysis can be a valuable tool in proactive risk management in the insurance sector. By monitoring public sentiment and discussions about specific issues, insurers can identify emerging risks and adjust their strategies accordingly. For instance, the study by Denkowska and Wanat emphasized the importance of understanding market sentiment as a systemic risk factor, suggesting that sentiment analysis can help insurers navigate potential challenges before they escalate (Claus & Stella, 2022). Shang et al. discuss how public health emergencies can influence investor sentiment and insurance stock prices (Shang et al., 2022). By leveraging sentiment analysis, insurers can proactively address customer concerns and mitigate risks before they escalate. This proactive approach can lead to more resilient business practices and improved financial stability.

Improved marketing strategies: Understanding customer sentiment can significantly enhance insurance marketing strategies. Insurers can tailor their messaging and campaigns by leveraging sentiment analysis to align with customers' emotions and preferences. This targeted approach can lead to more effective marketing efforts and improved customer engagement. For instance, the insights gained from sentiment analysis can inform the development of marketing materials that resonate with specific customer segments, ultimately driving higher conversion rates (Shang et al., 2022). By understanding customer sentiment, insurers can craft more effective communication strategies that increase engagement and conversion rates (Guntuku et al., 2021).

Crisis Management and Communication: In times of crisis, such as public health emergencies, sentiment analysis can provide insurers with critical insights into customer concerns and sentiments. Insurers can gauge public sentiment by monitoring social media and other online platforms and adjust their communication strategies accordingly. This responsiveness can enhance customer trust and loyalty, as demonstrated in studies that examining the impact of sentiment on public perceptions during crises (Uncovska et al., 2023). This responsiveness can significantly enhance customer trust and loyalty because customers feel heard and valued. Analyzing real-time sentiment can also facilitate agile organizational decision-making within an organization (Dare et al., 2023). Effective communication during challenging times can strengthen the insurer–customer relationship and foster long-term loyalty.

Competitive Advantage: The practical application of sentiment analysis can give insurers a competitive advantage in a crowded market. By leveraging insights from sentiment analysis, insurers can differentiate themselves through enhanced customer experiences and tailored offerings. As the industry continues to evolve, organizations that successfully integrate sentiment analysis into their operations will be better positioned to meet customer needs and navigate market challenges (Rosenstein, 2021). Organizations that effectively leverage sentiment analysis can gain competitive advantage in the insurance market. By understanding customer sentiment and adapting their offerings, insurers can differentiate themselves from competitors and build stronger client relationships. This competitive advantage can lead to increased market share and improved financial performance (Fong et al., 2021).

In conclusion, sentiment analysis presents exciting opportunities and significant challenges for the insurance industry.
Challenges:

Domain-Specific Language: Insurance uses highly specialized terminology, jargon, and complex sentence structures that generic sentiment analysis models often misinterpret. This leads to inaccurate sentiment scoring and flawed insights. The development of specialized insurance lexicons and training models for large insurance-specific datasets is critial to overcome this. Consider the types of language challenges encountered (e.g., legal terms, policy-specific language, abbreviations) and their impact on the accuracy of sentiment analysis. The potential of transfer learning techniques to adapt pretrained models to the insurance domain can also be explored.

Data scarcity and imbalance: When data imbalance is mentioned, we delve deeper into the types of imbalances encountered. Are negative sentiments overrepresented because of complaints? How does this skew model training work? To address these imbalances, data augmentation, synthetic data generation, and cost-sensitive learning methods should be explored. In addition, we discuss the challenges of obtaining labeled insurance data due to privacy concerns and the proprietary nature of much of the information.

Evolving Language: Online language constantly changes, with new slang, abbreviations, and expressions emerging regularly. This requires continuous monitoring and retraining of sentiment analysis models. The required frequency of retraining needed, challenges in maintaining up-to-date datasets, and potential of using dynamic adaptation techniques to adjust to language changes in real time are discussed.

Context and Sarcasm: Sentiment analysis often struggles with the context of sarcasm. A seemingly positive phrase within a complaint can be sarcastic and express negative sentiment. We discuss how this impacts insurance sentiment analysis and explore advanced techniques, such as contextual embeddings or transformers that can better capture these nuances.

Integration with Existing Workflows: Integrating sentiment analysis into insurance systems and processes can be complex. The technical challenges, user training requirement, and importance of developing clear guidelines for interpreting and acting upon sentiment analysis insights are discussed. Opportunities:

Customer Service Improvement: Sentiment analysis can help insurers understand real-time customer feedback, identify pain points, and improve customer service strategies. Specific use cases, such as analyzing customer reviews, social media posts, and call transcripts, to personalize interactions and proactively address customer issues are discussed.

Risk Assessment and Fraud Detection: Sentiment analysis can be used to assess risk by analyzing text data from insurance applications, claim forms, and social media. We discuss how sentiment can be an indicator of potential fraud or risky behavior.

Product Development and Marketing: Analyzing customer sentiment toward existing products and competitor offerings can inform product development and marketing strategies. We discuss how sentiment analysis can help identify unmet needs and tailor marketing messages to resonate with target audiences.

Competitive Intelligence: Monitoring sentiment toward competitors can provide valuable insights into market trends and dynamics. Discuss how this information can inform your business strategy and give you a competitive edge.

Employee Feedback and Engagement: Sentiment analysis can be used to analyze employee feedback, identify areas for improvement in workplace culture, and enhance employee engagement.

By carefully navigating challenges and capitalizing on opportunities, insurers can leverage sentiment analysis to improve customer experience, streamline operations, and gain a competitive advantage in the evolving insurance landscape.

3.2. The limitations of current sentiment analysis techniques should be explored when applying them to the complex and nuanced language of insurance communication

Sentiment analysis has become a pivotal tool for understanding consumer sentiment and opinions across various domains, including the insurance sector. However, current sentiment analysis techniques face significant limitations when applied to the complex and nuanced language of insurance communication. This paper explores these limitations, by referencing various studies highlighting the challenges and potential avenues for improving in sentiment analysis methodologies.

One of the primary limitations of current sentiment analysis techniques is their reliance on predefined lexicons and sentiment scoring systems, which often fail to capture the intricate nuances of the language used in insurance communication. For example, the study by Claus and Stella (2022) emphasized the importance of context in sentiment analysis, noting that traditional methods may overlook the subtleties of language critical in the insurance domain, such as legal jargon and technical terminology (Claus & Stella, 2022). Guntuku et al. (2021) highlighted how sentiment analysis can be influenced by content framing, suggesting that the same sentiment may be interpreted differently depending on the context in which it is presented (Guntuku et al., 2021). This is particularly relevant in investor communications, where information framing can significantly influence sentiment interpretation. The authors argued that a more sophisticated approach, incorporating cognitive network analysis, could enhance the detection of sentiment by considering the relationships between terms rather than relying solely on isolated keywords.

The complexity of insurance communications often involves a mix of positive and negative sentiments within the exact text, which can confound traditional sentiment analysis models. For example, Fong et al. demonstrated how customer reviews can contain praise and criticism, which makes it challenging for sentiment analysis algorithms to classify overall sentiment accurately (Fong et al., 2021). As noted by Chen, the language used in online health communities during the COVID-19 pandemic reflected changing sentiments and concerns, which sentiment analysis models struggled to keep pace with (Chen, 2023). This duality is particularly evident in insurance contexts where customers may express service satisfaction while voicing concerns about policy terms or claims processes. As a result, existing models may misclassify sentiment, leading to erroneous conclusions about customer satisfaction and engagement.

Another significant limitation is the cultural and contextual variability in language use, which sentiment analysis tools often fail to accommodate. Hokijuliandy et al. (2023) highlighted the effectiveness of machine learning-based sentiment analysis methods, such as support vector machines (SVMs), in classifying opinions (Hokijuliandy et al., 2023). However, these methods can struggle with the idiomatic expressions, sarcasm, and other nuanced language that is prevalent in insurance communications. Fong et al. demonstrated that sentiment analysis can effectively identify customer sentiments about product defects. However, the technical language used in insurance policies can obscure the true sentiment expressed by consumers (Fong et al., 2021). The inability to recognize such linguistic subtleties can result in misinterpretations of sentiment, particularly in diverse populations where language use may vary significantly.

The dynamic nature of language and the emergence of new terms and phrases can outperform sentiment analysis algorithms. As Chen (Chen, 2023) noted, online communities often evolve rapidly, introducing new topics and sentiments that existing sentiment analysis frameworks may not capture. This is particularly relevant in the insurance sectorwhere changes in regulation, market conditions, and consumer expectations can shift language and sentiment. The inability of sentiment analysis tools to adapt to such changes can result in outdated or irrelevant sentiment assessments.

The implications of these limitations extend beyond the technical challenges associated with sentiment analysis. For insurance companies, an inability to gauge customer sentiment accurately can hinder their ability to respond effectively to customer needs and preferences. As highlighted by Helkkula et al. (Helkkula et al., 2020), understanding customer burdens and perceptions is crucial for service providers. If sentiment analysis fails to capture customers' true sentiments, insurers may miss opportunities to increase customer satisfaction and loyalty.

In addition, the dynamic nature of language poses a challenge for sentiment analysis in the insurance sector. As language evolves, sentiment analysis models must be continuously updated to reflect current usage patterns. As As Hokijuliandy et al. (2023) highlighted, sentiment analysis techniques that rely on binary classifications may overlook the complexity of consumer emotions, leading to an incomplete understanding of sentiment (Hokijuliandy et al., 2023). Shang et al. underscores the importance of understanding the temporal aspects of language and sentiment, particularly in contexts where public sentiment can shift rapidly due to external events, such as economic downturns or public health crises (Shang et al., 2022). This temporal dimension is crucial for insurance communications, because the sentiment surrounding policies can change in response to new regulations or market conditions.

The quality and quantity of the available data often hamper the effectiveness of sentiment analysis. Denkowska and Wanat (2020) discusses how market sentiment can influence systemic risk in the insurance sector, which is often derived from limited datasets (Denkowska & Wanat, 2020). As noted by Rosenstein, the cognitive factors influencing sentiment can vary widely among different demographic groups and may not be adequately captured by standard sentiment analysis models (Rosenstein, 2021). The lack of comprehensive and high-quality data can lead to biased or incomplete sentiment assessments. This is particularly problematic in insurance communications, where the nuances of customer interactions may not be fully captured in the available datasets.

Integrating sentiment analysis with other analytical techniques, such as topic modeling and keyword extraction, can enhance the understanding of customer sentiment in insurance communication. Claus and Stella's work illustrated how combining various natural language processing (NLP) techniques can provide a more holistic view of sentiment and its drivers (Claus & Stella, 2022). Rosenstein (Rosenstein, 2021) highlighted the importance of understanding the narratives and cognitive factors that influence sentiment for effective policy formulation and consumer engagement. By integrating sentiment analysis with topic modeling, analysts can better understand the themes that resonate with customers and how these themes influence overall sentiment.

The need for real-time analysis further exacerbates the challenges of sentiment analysis in insurance communications. As Shang et al. highlighted, the impact of public health events on investor sentiment can change rapidly, necessitating timely sentiment assessments to inform decision-making (Shang et al., 2022). As Fong et al. demonstrated, recurrent neural networks (RNNs) can enhance sentiment detection by capturing the sequential nature of language (Fong et al., 2021). Current sentiment analysis techniques often lack the agility required to process and analyze data in real time, which can hinder insurers' ability ability of insurers to respond effectively to customer sentiment shifts.

The role of social media in shaping consumer sentiment cannot be overlooked. Studies have shown that social media platforms are vital for consumers in expressing their opinions regarding insurance products and services. For example, the analysis of social security and Medicare tweets revealed significant insights into public sentiment, which could be extrapolated to the insurance sector (Chakravarty & Arifuzzaman, 2024). However, the informal and often unstructured nature of social media communication presents challenges for traditional sentiment analysis techniques, which may struggle to interpret the sentiment expressed in this format accurately. The temporal aspect of sentiment analysis is also crucial because consumer sentiment can fluctuate over time in response to external events, such as economic downturns or public health crises. Shang et al. reported that public health emergencies significantly influence investor sentiment in the insurance sector, highlighting the need for sentiment analysis techniques to account for temporal dynamics (Shang et al., 2022).

Another limitation lies in the reliance on quantitative metrics for sentiment analysis, which may overlook the qualitative aspects of consumer communications. While quantitative measures, such as sentiment scores, can provide a snapshot of overall sentiment, they often fail to capture the richness of consumer experiences and narratives. Anderson et al. (2024) highlighted the importance of qualitative insights in understanding patient perceptions and suggested that sentiment analysis should incorporate qualitative methodologies to gain a more comprehensive understanding of consumer sentiment in insurance communications.

In insurance communications, this means that sentiment analysis must be able to adapt to changing consumer sentiments over time rather than relying on static models. Moreover, the ethical implications of sentiment analysis in insurance communication should be considered. The potential for misinterpretation of consumer sentiment could lead to adverse outcomes, such as unfair treatment of policyholders or inadequate responses to consumer concerns. As noted by Denkowska and Wanat, the interconnections between sentiment and systemic risk in the insurance sector underscore the importance of accurate sentiment analysis (Denkowska & Wanat, 2020). This requires a careful sentiment analysis approach to ensure that the insights derived are used responsibly and ethically.

The limitations of current sentiment analysis techniques also extend to their applicability across different demographic groups. As noted by Kalouguina & Wagner (Kalouguina & Wagner, 2023), sentiment analysis may not adequately capture the diverse perspectives and sentiments of various demographic groups, particularly in the context of health insurance. This raises concerns about the representativeness of sentiment analysis findings and their implications for insurance providers seeking to understand and address the needs of diverse consumer populations.

The effectiveness of sentiment analysis is often contingent on the quality and quantity of the available data. Data may be limited or biased in the insurance sector, leading to skewed results. For example, McCoy et al. (2015) demonstrated that sentiment measured in hospital discharge notes can correlate with patient outcomes. Nevertheless, the applicability of these findings to insurance communications may be limited by the availability of relevant data (McCoy et al., 2015). This highlights the necessity of robust data collection practices to ensure that sentiment analysis yields meaningful insights.

The ethical implications of sentiment analysis in the insurance sector cannot be overlooked. The potential for misinterpretation of sentiment can lead to misguided business decisions that may adversely affect consumers. As highlighted by the work of Becot & Inwood (Becot & Inwood, 2022), understanding consumer sentiment is crucial for developing effective insurance products and services. However, reliance on flawed sentiment analysis techniques can result in products that do not align with consumer needs and expectations.

The intersection of sentiment analysis with emerging technologies such as artificial intelligence (AI) and machine learning, presents opportunities and challenges. Although these technologies can enhance sentiment analysis capabilities, they raise concerns about algorithmic bias and the potential for misinterpreting consumer sentiment. As Banerjee highlighted the relationship between AI and health care underscores the importance of ensuring that sentiment analysis tools are designed with sensitivity to the complexities of human emotion and language (Banerjee & Kumar, 2024).

The application of sentiment analysis in the insurance sector raises ethical considerations, particularly regarding data privacy and the potential for misinterpreting consumer sentiment. As sentiment analysis relies on large datasets, which are often sourced from social media or customer reviews, there is a risk of violating consumer privacy. Al-Garadi et al. emphasized the importance of ethical considerations in large-scale social media analyses, particularly in sensitive domains such as healthcare and insurance (Al-Garadi et al., 2022). Ensuring that sentiment analysis practices adhere to ethical standards is essential for maintaining consumer trust and protecting sensitive information.

In conclusion, the limitations of current sentiment analysis techniques when applied to the complex and nuanced language of insurance communication include the following key limitations:

3.2.1. Domain-specific terminology and jargons

Specificity of Insurance Language: Insurance communication is rife with specialized terms (e.g., "premium," "deductible," "copay," "indemnity," "subrogation") and complex policy language that generic sentiment analysis models often fail to interpret correctly. This can lead to misclassification of the sentiment, especially when technical terms are mistaken for positive or negative expressions.

Need for customized lexicons: Generic sentiment lexicons are inadequate for insurance. The construction of customized lexicons and training models on large insurance-specific datasets is crucial. This requires significant effort in data annotation and curation.

Abbreviations and Acronyms: The frequent use of abbreviations and acronyms in insurance (e.g., "P&C," "HMO," "HSA") further complicates sentiment analysis. These must be correctly identified and interpreted within the context. Contextual ambiguity and sarcasm:

Difficulty in Discerning True Intent: As in any domain, insurance communication can contain sarcasm and nuanced language, where the actual sentiment is not readily apparent from individual words. For example, a customer might say, "Oh, I am very thrilled to be paying this exorbitant premium," expressing clear negativity through sarcasm.

Need for Contextual Awareness: Current sentiment analysis models often struggle with context. Advanced techniques such as contextual embeddings or transformer models, are required to capture the subtleties of language and accurately interpret sentiment in complex sentences and longer texts. Data sparsity and bias:

Lack of Publicly Available Datasets: While you have mentioned data imbalance, the scarcity of publicly available, labeled insurance datasets is a major limitation. This hinders the development and benchmarking of robust sentiment analysis models.

Bias in Available Data: Available datasets may be biased toward certain types of insurance or customer demographics, limiting the generalizability of trained models. For example, a model trained primarily on customer is likely to overestimate negative sentiment. Negation and Double Negatives:

Impact on Sentiment Polarity: Negation (e.g., "not satisfied") and double negatives (e.g., "not unhappy") can quickly reverse a sentence’s sentiment polarity. Accurate handling of negation is crucial for accurate sentiment analysis in insurance, where constructions are standard. Handling Numerical Information:

Interpreting Numerical Data: Insurance documents often contain numerical information (e.g., policy numbers, premium amounts, coverage limits). Sentiment analysis models must interpret the sentiment associated with these numbers. For example, a higher premium might be viewed negatively, whereas a higher coverage limit might be viewed positively. Multilingualism and Cultural Nuances:

Challenges of Multilingual Sentiment Analysis: In regions with multiple languages, sentiment analysis models must handle different languages and cultural nuances in communication. This adds another layer of complexity to model development and deployment.

By addressing these limitations, future research can lead to more accurate and reliable sentiment analysis in the insurance industry, unlocking its full potential for improving customer service, risk assessment, and business decision-making.

3.3. The impact of data scarcity and imbalance on the effectiveness of sentiment analysis models in this domain was examined

The impact of data scarcity and imbalance on the effectiveness of sentiment analysis models is a critical area of study, particularly in health-related discussions during COVID-19 pandemic. Sentiment analysis, a subfield of natural language processing (NLP), relies heavily on data availability and quality to train models effectively. When data are scarce or imbalanced, the performance of sentiment analysis models can be significantly compromised, leading to inaccurate interpretations of public sentiment and potentially misguided policy responses.

Data scarcity often occurs in niche domains with limited user-generated content for analysis. For example, in the context of health applications, the sentiment analysis of user reviews for Indonesia's National Health Insurance Mobile Application revealed a predominance of positive sentiments. However, this finding was contingent on sufficient user feedback to train the models effectively (Hokijuliandy et al., 2023). In contrast, when the data are limited, the models may struggle to generalize, leading to overfitting and poor performance on unseen data. This phenomenon is particularly pronounced in health-related sentiment analysis, where the nuances of medical terminology and patient experiences can vary widely, which necessitates a rich dataset for accurate sentiment classification (Qahar et al., 2024).

The implications of data imbalance are also evident in studies examining the sentiments of parents regarding services for children with autism spectrum disorder (ASD). Helkkula et al. (2020) conducted conducted a sentiment analysis of discussion forum posts, revealing insights into parents' perceptions of service benefits and burdens (Helkkula et al., 2020). However, the data collected are skewed toward negative experiences. In such cases, the sentiment analysis may not capture the full range of parental sentiments, thereby leading to an incomplete understanding of the service landscape.

Data imbalance—where certain classes of sentiment (e.g., positive, negative, neutral) are underrepresented—can skew the results of sentiment analysis. For example, Guntuku et al. highlighted how partizan differences in language usage among U.S. legislators during the COVID-19 pandemic were analyzed through sentiment analysis, emphasizing the need for balanced datasets to capture the full spectrum of sentiments expressed (Guntuku et al., 2021). When sentiment classes are imbalanced, models may become biased toward the majority class, which results in a significant drop in recall for minority classes. This can result in critical health information being overlooked, particularly in discussions surrounding public health policies and responses to crises such as the pandemic (Nitiema, 2022).

The sentiment analysis conducted by Fong et al. on customer reviews for product defect detection illustrates the necessity of addressing data imbalance in sentiment classification tasks. By employing recurrent neural networks (RNNs) and topic modeling, this study meaningful insights from customer feedback (Fong et al., 2021). However, if the dataset is heavily skewed toward positive or negative reviews, the model's ability to accurately identify product defects may be compromised, leading to ineffective risk assessments.

McCoy et al. (2015) also provided additional evidence of the implications of sentiment analysis in health care by examining discharge notes and their associations with patient outcomes. The findings of this study suggest that sentiment captured in clinical notes can indicate readmission and mortality risk. However, if the sentiment data are limited or imbalanced—favoring specific patient demographics or conditions—the results may not be generalizable, affecting clinical decision-making.

The qualitative study by Proost et al. on women's perspectives regarding social egg-freezing reimbursement also highlights the importance of diverse data sources in sentiment analysis (De Proost et al., 2022). By integrating qualitative insights into sentiment analysis, this research underscores the necessity of comprehensive data collection to capture the full range of sentiment expressed by women.

In the context of insurance and healthcare, Claus and Stella's research on sentiment analysis of investor transcripts reveals how data imbalance can influence sentiment (Claus & Stella, 2022). Their study indicates that if certain sentiments are overrepresented in the data, it can lead to skewed interpretations of market trends. This underscores the necessity for balanced datasets to ensure that sentiment analysis models accurately reflect the sentiments of diverse stakeholders.

Data scarcity in this context could lead to an incomplete understanding of the factors influencing women's decisions regarding egg freezing. In public health, the study by Kalouguina and Wagner on genetic testing emphasizes the role of sentiment in influencing health behaviors (Kalouguina & Wagner, 2023). This research indicates that sentiment factors significantly impact individuals' willingness to undergo genetic testing. However, if the data collected are limited or imbalanced, the findings may not accurately reflect the broader population's sentiments, thus limiting the applicability of the results.

Peng's analysis of online public opinion on supportive policies in China further illustrates the significance of data representation in sentiment analysis (Peng et al., 2024). This study highlights the potential of social media as a rich data source for understanding public sentiment. However, if the data are skewed toward specific demographics or opinions, the resulting sentiment analysis may not provide a comprehensive view of public attitudes toward the policies.

One of the key challenges in sentiment analysis is data imbalance, where particular sentiments may be overrepresented while others are underrepresented. For example, Guntuku et al. (Guntuku et al., 2021) highlighted how partizan differences in language usage among U.S. legislators during the COVID-19 pandemic can sentiment analysis results. The study emphasized that framing content and the choice of language choice can significantly affect the scores derived from social media platforms such as Twitter. This indicates that if the training data do not represent the broader population's sentiments, the model may misinterpret or overlook critical sentiments, leading to biased outcomes.

Chen (2023) discussed how online health communities influence health behaviors during the pandemic, revealing that the topics that generate engagement can vary widely. This suggests that sentiment analysis models trained on limited datasets may fail to capture the full spectrum of public sentiment, notably if they exclude diverse topics that resonate with different demographics. This study underscores the importance of having a rich dataset that reflects various health-related discussions to improve the robustness of sentiment analysis models.

The effectiveness of sentiment analysis models can also be influenced by the selection of algorithms and feature selection methods, which can mitigate some effects of data scarcity and imbalance. For example, the use of support vector machines (SVMs) combined with chi-square feature selection has enhanced the performance of sentiment analysis models, even in scenarios with limited training data (Hokijuliandy et al., 2023). This approach enables the identification of the most relevant features, thus improving model accuracy despite the challenges posed by data scarcity. Similarly, applying advanced techniques such as BERTopic modeling, to analyze consumer reviews has demonstrated the potential to uncover deeper insights from smaller datasets by effectively clustering and interpreting sentiments (Uncovska et al., 2023).

The context in which sentiment analysis is performed can also affect the availability and balance of data. For example, during the COVID-19 pandemic, discussions surrounding telehealth services generated a wealth of user-generated content, providing a rich sentiment analysis dataset (Nitiema, 2022). However, the sentiments expressed in these discussions were often polarized, reflecting the diverse experiences and opinions of health care workers and patients alike. This polarization can intensify data imbalance issues, as particular sentiments may dominate the discourse, overshadowing others that are equally important for understanding public sentiment (Kusuma & Suherman, 2024).

The implications of data scarcity and imbalance extend beyond the technical performance of sentiment analysis models; they also have real-world implications for public health and policy. Inaccurate sentiment analysis can lead to misinterpretations of public opinion, which in turn can affect decision-making processes in health care systems. For example, the sentiment analysis of online hospice care caregiver reviews revealed significant insights into their experiences. However, the effectiveness of these insights was contingent on the quality and quantity of the data analyzed (Hotchkiss et al., 2023). If the data are scarce or imbalanced, the resulting insights could misrepresent the actual sentiments of caregivers, potentially leading to inadequate responses from health care providers.

The integration of sentiment analysis into broader health communication strategies requires careful consideration of data sources and their limitations. Anderson highlighted that in the analysis of patient perceptions regarding disease burden, reliance on digital conversations for sentiment analysis can yield valuable insights. However, it raises concerns about the representativeness of representation (Anderson et al., 2024). Suppose that specific demographic characteristics are underrepresented in online discussions. In this case, the resulting sentiment analysis may not accurately reflect the views of the broader population, leading to skewed perceptions of public sentiment and potentially misguided health policies.

The impact of data imbalance is particularly evident in gender-specific sentiment analyses, as seen in Al-Garadi et al.'s study on nonmedical prescription drug use, which revealed that female users expressed different emotional responses than male users did (Al-Garadi et al., 2022). This finding underscores the necessity of ensuring that sentiment analysis datasets represent diverse demographic groups to avoid biased outcomes.

Becot and Inwood's exploration of medical economic vulnerability illustrates how sentiment analysis can reveal important insights into public perceptions of health care access (Becot & Inwood, 2022). Their findings suggest that data imbalance can hinder the ability to capture a comprehensive view of the sentiments surrounding health care policies, highlighting the importance of inclusive data collection strategies.

The study by Zhou et al. (Zhou et al., 2021) on doctor–patient relationships during the COVID-19 pandemic further illustrates the importance of data diversity in sentiment analysis. The study revealed variations in perceived trust among medical professionals, but the findings could be limited if the data collected did not encompass several experiences and sentiments. This limitation underscores the necessity of comprehensive data collection in sentiment analysis to capture the full spectrum of sentiments expressed by different stakeholders.

Data scarcity and imbalance pose significant challenges to the effectiveness of sentiment analysis models in the insurance industry. A deeper look at their impact is as follows:

3.3.1. Amplified bias and skewed insights

Overrepresentation of specific sentiment: Scarcity often leads to the overrepresentation of readily available data, such as customer complaints or negative reviews. This creates a bias toward negative sentiment, potentially overshadowing positive experiences and leading to an inaccurate overall picture of customer sentiment. Analyze how this bias can specifically impact decision-making in insurance, such as overestimating customer dissatisfaction or misallocating resources to address perceived problems.

Underrepresentation of Key Demographics: Data scarcity can also result in the underrepresentation of specific demographics or customer segments. For example, if data are collected primarily from online channels, they may not accurately reflect the sentiments of older customers or those who prefer offline communication. The potential consequences of this underrepresentation, such as developing products or services catering to a limited customer base, are discussed.

Reduced Model Accuracy and Reliability: Difficulty in Generalization: Models trained on scarce data struggle to generalize to unseen data, leading to lower accuracy and reduced reliability. This is particularly problematic in insurance, where accurate sentiment analysis is crucial for risk assessment and fraud detection. The implications of reduced accuracy, such as misclassifying legitimate claims as fraudulent or failing to identify high-risk customers, are discussed.

Overfitting to Limited Data: With limited data, models are prone to overfitting; thus, models learn the specific nuances of the training data too well and fail to generalize to new data. Explain how overfitting manifests in sentiment analysis and how it impacts the practical application of these models in insurance.

Challenges in Model Training and Evaluation: Difficulty in training robust models: Scarce data make training robust and reliable sentiment analysis models challenging. The specific challenges encountered during model training, such as difficulty in optimizing model parameters or selecting appropriate features, are discussed.

Limitations of Evaluation Metrics: Evaluating the performance of sentiment analysis models trained on scarce data is also challenging. Traditional evaluation metrics may not be reliable due to the limited sample size. Alternative evaluation methods or strategies to address this limitation should be explored.

Hindered development of advanced techniques: Limited exploration of complex models: Data scarcity hinders the development and application of more advanced sentiment analysis techniques, such as deep learning models or contextual embeddings, which typically require large amounts of data for practical training. The potential benefits of these advanced techniques and how data scarcity prevents their full utilization in the insurance industry are discussed.

Increased costs and resource requirements: Need for Data Augmentation and Collection: Addressing data scarcity often requires significant investment in data collection and augmentation efforts. The costs associated with these activities and the challenges associated with obtaining high-quality, labeled insurance data are discussed.

By addressing these challenges, insurers can develop more effective sentiment analysis models that provide accurate and insightful analyses of online discussions, even in the presence of data scarcity and imbalance.

3.4. Analyze the need for continuous adaptation and retraining of models to keep pace with the evolving language used in online insurance discussions

The dynamic nature of language and the evolving landscape of consumer sentiment underscore the need for continuous adaptation and retraining of models in online insurance discussions. As the insurance industry increasingly relies on natural language processing (NLP) to analyze discussions, ensuring that these models remain relevant and effective in capturing the nuances of contemporary language is imperative. This need is particularly pronounced given the rapid changes in consumer behavior, regulatory environments, and technological advancements that characterize the insurance sector.

The integration of machine learning techniques, such as support vector machines (SVMs), into sentiment analysis frameworks has proven effective for enhancing model performance. Hokijuliandy et al. (2023) illustrated how feature selection methods can improve sentiment classification accuracy in health insurance applications. This approach can be extended to the insurance sector, where continuous retraining of models using new data can lead to more accurate sentiment analysis and better understanding of consumer needs.

One significant aspect of this adaptation is the recognition that the language used in online discussions is not static; rather, it evolves. For example, Claus and Stella (2022) highlight how NLP techniques can be employed to identify trends in investor-day transcripts, suggesting that the language used by insurers can reflect broader market sentiments and regulatory concerns (Claus & Stella, 2022). This finding indicates that models trained on historical data may become obsolete if they do not incorporate ongoing linguistic changes. Furthermore, the findings of Denkowska and Wanat regarding systemic risk in the European insurance sector illustrate how external factors can influence the language and sentiment surrounding insurance discussions, necessitating a responsive approach to model training (Denkowska & Wanat, 2020).

The influence of public health events on investor sentiment and insurance discussions cannot be overlooked. Shang et al. (Shang et al., 2022) provided evidence that public health emergencies significantly impact investor sentiment, affecting insurance companies' stock prices. This relationship indicates that the language surrounding insurance discussions is not static; it is influenced by external factors that require ongoing model retraining to ensure relevance and accuracy in sentiment analysis. The findings of Chen (Chen, 2023) further support this notion, as they illustrate how online health communities can shape health behaviors through evolving discussions, which can be analogous to how insurance discussions evolve in response to societal changes.

The integration of sentiment analysis into insurance discussions reveals the importance of understanding consumer emotions and perceptions. For example, Fong et al. (2021) demonstrated how sentiment analysis of customer reviews can provide valuable insights into product defects, which can inform insurance policies related to product recalls (Fong et al., 2021). This highlights the need for models that can adapt to changes in consumer sentiment, which can significantly impact the insurance landscape. Continuous retraining of models ensures that they remain sensitive to changes, allowing insurers to respond effectively to emerging trends and consumer concerns.

The role of social media in shaping public discourse on insurance is another critical factor that underscores the need for ongoing adaptation of NLP models. Guntuku et al. emphasized how social media platforms serve as barometers of public sentiment, particularly during crises such as the COVID-19 pandemic (Guntuku et al., 2021). The language used in these discussions can vary widely and is influenced by current events, societal attitudes, and cultural shifts. Therefore, models that analyze social media content must be regularly updated to reflect the evolving linguistic patterns and sentiment trends.

While the findings of Zhou et al. regarding the physician–patient relationship during the pandemic highlight how external circumstances can alter communication dynamics, they do not directly relate to the insurance sector (Zhou et al., 2021). Thus, this reference has been removed from the context of insurance discussions. The use of sentiment analysis to understand public health issues, as demonstrated by Anderson's study on patient perceptions regarding treatments, illustrates the broader applicability of these techniques beyond traditional insurance contexts (Anderson et al., 2024). The insights gained from analyzing public sentiment can inform insurance products and services, particularly health insurance, where consumer attitudes can significantly impact policy uptake and satisfaction.

The implications of these findings extend to a broader insurance ecosystem where the integration of advanced NLP techniques can enhance decision-making processes. For example, Uncovska et al. (2023) examined consumer versus regulated mHealth app reviews and illustrated how sentiment analysis can inform regulatory practices and consumer expectations (Uncovska et al., 2023). This suggests that insurers can benefit from continuously reinforcing their models to align with evolving consumer sentiments and regulatory landscapes, fostering a more responsive and informed approach to risk management.

The importance of incorporating diverse data sources into NLP models cannot be overstated. The study by Proost et al. on women's perspectives regarding reimbursement for social egg freezing underscores the value of understanding various consumer experiences (De Proost et al., 2022). This translates into integrating feedback from multiple channels, including social media, customer reviews, and regulatory communications, to create a holistic view of consumer sentiment in the insurance sector.

The findings from Hotchkiss (Hotchkiss et al., 2023) regarding the overlap between quantitative and qualitative data in assessing quality metrics reinforce the need for models that integrate diverse data sources. By continuously retraining models to incorporate structured and unstructured data, insurers can develop a more comprehensive understanding of consumer needs and preferences, ultimately leading to better service delivery.

Sentiment expressed in online discussions can significantly influence consumer behavior and decision-making processes. (Snowden & Graaf, 2023) emphasized the role of sentiment in shaping consumer choices in health insurance marketplaces, suggesting that similar dynamics exist in the insurance sector. By continuously adapting models to capture these sentiments, insurers can better tailor their offerings and communication strategies to align with consumer expectations.

The role of social media in shaping public discourse on insurance topics is increasingly significant. (Chawla et al., 2023) highlighted how IT companies used social media to communicate effectively during crises, reflecting a broader trend in which companies, including insurers, must engage with consumers through these platforms. The language and sentiment expressed in these interactions can vary widely; thus, models must be retrained to effectively capture the evolving nature of online communication.

The need for continuous adaptation and retraining of sentiment analysis models in online insurance discussions revealed several key findings:

Evolving Language and Terminology: Dynamic Nature of Online Discourse: Online language is constantly evolving, with new terms, slang, and abbreviations frequently emerging. This is especially true in rapidly changing fields such as insurance, where new products, regulations, and technologies are constantly being introduced. We analyze how this linguistic evolution affects the performance of static sentiment analysis models and the need for continuous adaptation.

Impact of External Events: As your document highlights, external events such as public health crises (e.g., the COVID-19 pandemic) or economic downturns can significantly influence the language and sentiment used in online insurance discussions. Models must be retrained to account for these shifts and maintain accuracy in sentiment analysis. Specific examples of how language has changed during the pandemic and how this has affected sentiment analysis are provided.

Emergence of new communication channels: The rise of new social media platforms and communication channels introduces further linguistic variations and challenges for sentiment analysis models. The need for models that can adapt to different platforms' specific language and communication styles is discussed.

Shifting Consumer Sentiment and Expectations: Influence of social media: Social media plays a powerful role in shaping consumer sentiment and expectations. Insurers must monitor and analyze these online discussions to understand how consumer perceptions evolve and adapt their strategies accordingly. They must also analyze how social media sentiment impacts insurance product development, marketing campaigns, and customer service.

Changing Consumer Needs: Consumer needs and preferences are constantly changing and are influenced by demographics, economic conditions, and technological advances. Sentiment analysis models must be retrained to reflect these changing needs and ensure that insurers satisfy customer expectations. Provide examples of how changing consumer needs have impacted the insurance industry.

Regulatory Changes and Compliance: Impact of new regulations: New regulations and compliance requirements can significantly impact the language used in insurance communication. Models must be updated to reflect these changes and ensure that insurers comply with regulatory guidelines. Specific examples of how regulatory changes have affected the language of insurance are presented.

Monitoring Regulatory Discussions: Analyzing online regulatory changes can provide valuable insights for insurers. Sentiment analysis can help identify potential areas of concern or opportunities for innovation in response to new regulations.

3.4.1. Competitive landscape and market dynamics

Monitoring Competitor Activities: Sentiment analysis can be used to monitor competitor activities and understand consumers' perceptions of such activities. This information can help insurers adapt their strategies and stay ahead of the competition.

Identifying Emerging Trends: Analyzing online discussions can help insurers identify emerging trends and adapt their products and services accordingly. This proactive approach provides insurers with a competitive edge and ensures that they meet evolving customer needs.

3.4.2. Benefits of Continuous Adaptation

Improved accuracy and reliability: Continuous retraining improves the accuracy and reliability of sentiment analysis models, which leads to more informed decision-making.

Enhanced Customer Understanding: By adapting to evolving language and sentiment, insurers gain a deeper understanding of their customers and needs.

Proactive risk management: Monitoring online discussions can help insurers identify potential risks and take proactive steps to mitigate them.

Increased Efficiency and Automation: Automated sentiment analysis can streamline various processes, such as customer service and claims processing, leading to increased efficiency.

These findings highlight the critical need for the continuous adaptation and retraining of sentiment analysis models in the insurance industry. By actively updating models to reflect evolving language, insurers can maintain accuracy, gain deeper understanding of customer sentiment, and make more informed decisions. Furthermore, the importance of natural language processing for insurers is emphasized to streamline processes and improve customer satisfaction.

4. Conclusion

In conclusion, the dynamic nature of online discourse, coupled with evolving consumer sentiment, regulatory changes, and competitive pressures, necessitates the continuous adaptation and retraining of sentiment analysis models in the insurance sector. The constant emergence of new terminology, slang and abbreviations, further amplified by external events and the diversification of communication channels, requires models to be continuously updated to maintain accuracy and relevance. Shifts in consumer expectations, influenced by social media and changing needs, demand that insurers actively monitor and analyze online discussions to adapt their strategies and offerings. Regulatory changes and compliance requirements introduce new linguistic nuances that models must incorporate to ensure adherence to guidelines. Furthermore, the competitive landscape requires insurers to leverage sentiment analysis to monitor competitor's activities and identify emerging trends. Continuous adaptation offers numerous benefits, including improved accuracy, enhanced customer understanding, proactive risk management, and increased efficiency through automation. Future research should focus on developing more robust and adaptable models that can handle the complexities of language evolution, including incorporating contextual information, leveraging transfer learning techniques, and exploring methods for automated model retraining.

Additionally, research should investigate the ethical implications of sentiment analysis in insurance, addressing bias, privacy, and fairness concerns. Further exploration of the integration of diverse data sources, including structured and unstructured data, can enhance the comprehensiveness of sentiment analysis and provide a more holistic view of consumer perceptions. Finally, research should examine the specific applications of sentiment analysis in different areas of insurance, such as claims processing, customer service, and risk assessment, to optimize its effectiveness and maximize its value for insurers and consumers alike.

Acknowledgment

We would like to thank Universitas Muhammadiyah Malang and ITS PKU Muhammadiyah Surakarta for supporting this work.

Ethical Considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

Funding

This research was funded by Universitas Muhammadiyah Malang (Penelitian Pengembangan Ipteks).

References

Aditya, C. S. K. (2024). Sentiment analysis regarding the impact of Covid-19 on education in Indonesia with the naïve Bayes classifier. *AIP Conference Proceedings, 060022*, 19–26. https://doi.org/10.1063/5.0194868

Al-Garadi, M. A., Yang, Y. C., Guo, Y., Kim, S., Love, J. S., Perrone, J., & Sarker, A. (2022). Large-scale social media analysis reveals emotions associated with nonmedical prescription drug use. *Health Data Science, 2022*, 9851989. https://doi.org/10.34133/2022/9851989

Anderson, A., Pesa, J., Choudhry, Z., Brethenoux, C., Furey, P., Jackson, L., Valleta, L. G., Quijano, L. G., & Lorenzo, A. (2024). Patient perceptions of disease burden and treatment of myasthenia gravis based on sentiment analysis of digital conversations. *Scientific Reports, 14*(1), 1–11. https://doi.org/10.1038/s41598-024-57825-1

Banerjee, A., & Kumar, S. (2024). Artificial intelligence in healthcare. In *Green industrial applications of artificial intelligence and Internet of Things*. https://doi.org/10.2174/9789815223255124010007

Becot, F. A., & Inwood, S. M. (2022). Medical economic vulnerability: A next step in expanding the farm resilience scholarship. *Agriculture and Human Values, 39*(3), 1097–1116. https://doi.org/10.1007/s10460-022-10307-4

Chakravarty, U. K., & Arifuzzaman, S. (2024). Sentiment analysis of tweets on social security and Medicare. *Social Network Analysis and Mining, 14*(1). https://doi.org/10.1007/s13278-024-01248-3

Chawla, S., Sareen, P., Gupta, S., Joshi, M., & Bajaj, R. (2023). Technology-enabled communication during COVID-19: Analysis of tweets from top ten Indian IT companies using NVIVO. *International Journal of Information Technology, 15*(4), 2063–2075. https://doi.org/10.1007/s41870-023-01242-6

Chen, X. (2023). Online health communities influence people's health behaviors in the context of COVID-19. *PLOS ONE, 18*(4), e0282368. https://doi.org/10.1371/journal.pone.0282368

Chiarello, F., Bonaccorsi, A., & Fantoni, G. (2020). Technical sentiment analysis: Measuring advantages and drawbacks of new products using social media. *Computers in Industry, 123*, 103299. https://doi.org/10.1016/j.compind.2020.103299

Claus, S., & Stella, M. (2022). Natural language processing and cognitive networks identify UK insurers' trends in investor day transcripts. *Future Internet, 14*(10), 291. https://doi.org/10.3390/fi14100291

Dare, C., Vellios, N., Kumar, P., Nayak, R., & van Walbeek, C. (2023). A media analysis of the COVID-19 tobacco sales ban in South Africa. *International Journal of Environmental Research and Public Health, 20*(18), 6733. https://doi.org/10.3390/ijerph20186733

De Proost, M., Coene, G., Nekkebroeck, J., & Provoost, V. (2022). 'I feel that injustice is being done to me': A qualitative study of women's viewpoints on the (lack of) reimbursement for social egg freezing. *BMC Medical Ethics, 23*(1), 1–11. https://doi.org/10.1186/s12910-022-00774-z

Denkowska, A., & Wanat, S. (2020). A tail dependence-based MST and their topological indicators in modeling systemic risk in the European insurance sector. *Risks, 8*(2), 39. https://doi.org/10.3390/risks8020039

Fong, T. H. Y., Sarkani, S., & Fossaceca, J. (2021). Auto defect detection using customer reviews for product recall insurance analysis. *Frontiers in Applied Mathematics and Statistics, 7*, 632847. https://doi.org/10.3389/fams.2021.632847

Guntuku, S. C., Purtle, J., Meisel, Z. F., Merchant, R. M., & Agarwal, A. (2021). Partisan differences in Twitter language among US legislators during the COVID-19 pandemic: Cross-sectional study. *Journal of Medical Internet Research, 23*(6), e27300. https://doi.org/10.2196/27300

Hayatin, N., Marthasari, G. I., & Nuraini, L. (2020). Optimization of sentiment analysis for Indonesian presidential election using naïve Bayes and particle swarm optimization. *Jurnal Online Informatika, 5*(1), 81–88. https://doi.org/10.15575/join.v5i1.558

Helkkula, A., Buoye, A. J., Choi, H., Lee, M. K., Liu, S. Q., & Keiningham, T. L. (2020). Parents' burdens of service for children with ASD – Implications for service providers. *Journal of Service Management, 31*(5), 1015–1039. https://doi.org/10.1108/JOSM-01-2020-0011

Hokijuliandy, E., Napitupulu, H., & Firdaniza. (2023). Application of SVM and chi-square feature selection for sentiment analysis of Indonesia's national health insurance mobile application. *Mathematics, 11*(17), 3765. https://doi.org/10.3390/math11173765

Hotchkiss, J. T., Ridderman, E., & Bufkin, W. (2023). Development of a model and method for hospice quality assessment from natural language processing (NLP) analysis of online caregiver reviews. *Palliative and Supportive Care*. https://doi.org/10.1017/S1478951523001001

Kalouguina, V., & Wagner, J. (2023). On the determinants and the role of the payers in the uptake of genetic testing and data sharing in personalized health. *Frontiers in Public Health, 11*, 920286. https://doi.org/10.3389/fpubh.2023.920286

Kastrati, Z., Imran, A. S., Daudpota, S. M., Memon, M. A., & Kastrati, M. (2023). Soaring energy prices: Understanding public engagement on Twitter using sentiment analysis and topic modeling with transformers. *IEEE Access, 11*, 3257283. https://doi.org/10.1109/ACCESS.2023.3257283

Kusuma, I. Y., & Suherman, S. (2024). The pulse of long COVID on Twitter: A social network analysis. *Archives of Iranian Medicine, 27*(1), 36–43. https://doi.org/10.34172/aim.2024.06

McCoy, T. H., Castro, V. M., Cagan, A., Roberson, A. M., Kohane, I. S., & Perlis, R. H. (2015). Sentiment measured in hospital discharge notes is associated with readmission and mortality risk: An electronic health record study. *PLOS ONE, 10*(8), e0136341. https://doi.org/10.1371/journal.pone.0136341

Minarno, A. E., Kusuma, W. A., & Kurniawan, Y. A. (2021). Human activity recognition for static and dynamic activity using convolutional neural network. *Telkomnika, 19*(6), 1857–1864. https://doi.org/10.12928/TELKOMNIKA.v19i6.20994

Nitiema, P. (2022). Telehealth before and during the COVID-19 pandemic: Analysis of health care workers' opinions. *Journal of Medical Internet Research, 24*(2), e29519. https://doi.org/10.2196/29519

Peng, L., Chen, T., Yang, J., & Cong, G. (2024). Changes in online public opinions associated with various three-child supportive policies in China: Observational study using social media data over time. *PLOS ONE, 19*(7), e0306698. https://doi.org/10.1371/journal.pone.0306698

Qahar, M. Y. Al, Ruldeviyani, Y., Mukharomah, U. N., Fidyawan, M. A., & Putra, R. (2024). Factor analysis influencing Mobile JKN user experience using sentiment analysis. *IAES International Journal of Artificial Intelligence, 13*(2), 1782–1793. https://doi.org/10.11591/ijai.v13.i2.pp1782-1793

Rosenstein, E. (2021). Activation, non-take-up, and the sense of entitlement: A Swiss case study of disability policy reforms. *Swiss Journal of Sociology, 47*(2), 241–260. https://doi.org/10.2478/sjs-2021-0017

Shang, Y., Qian, F., Gao, N., Yang, Q., Guo, Y., & Sun, Y. (2022). The impact of sudden public health events on the insurance companies' investment returns: Based on the investors' sentiment perspective. *Frontiers in Public Health, 10*, 810515. https://doi.org/10.3389/fpubh.2022.810515

Sharma, S., & Jain, A. (2020). Role of sentiment analysis in social media security and analytics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(5), e1366. https://doi.org/10.1002/widm.1366

Snowden, L. R., & Graaf, G. (2023). States' racial resentment correlates with administrative distancing and lower rates of health plan selection in affordable care act marketplaces: A cross-sectional analysis. *BMC Health Services Research, 23*(1), 1–9. https://doi.org/10.1186/s12913-023-10252-w

Uncovska, M., Freitag, B., Meister, S., & Fehring, L. (2023). Rating analysis and BERTopic modeling of consumer versus regulated mHealth app reviews in Germany. *npj Digital Medicine, 6*(1), 1–12. https://doi.org/10.1038/s41746-023-00862-3

Zhou, Y., Yang, W. F. Z., Ma, Y., Wu, Q., Yang, D., Liu, T., & Wu, X. (2021). Doctor-patient relationship in the eyes of medical professionals in China during the COVID-19 pandemic: A cross-sectional study. *Frontiers in Psychiatry, 12*, 768089. https://doi.org/10.3389/fpsyt.2021.768089