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Research Article

Sentiment analysis in FinTech: Trends and approaches in market, risk, and compliance

Finansal teknolojilerde duygu analizi: Pazar, risk ve uyum alanlarında eğilimler ve yaklaşımlar

Busra Ozdenizci Kose[1]

[1] Assoc. Prof., Department of Management Information Systems, Gebze Technical University, Kocaeli, Türkiye, busraozdenizci@gtu.edu.tr

ORCID: 0000-0002-8414-5252

Abstract

As the financial technology (FinTech) sector increasingly embraces data-driven strategies, sentiment analysis has emerged as a critical tool for extracting actionable insights from unstructured textual data. This study explores the strategic applications of sentiment analysis in FinTech, with a particular focus on its roles in market prediction, risk assessment, and regulatory compliance. Drawing on a systematic thematic analysis of the academic literature, this study synthesises how financial institutions utilise sentiment analysis to enhance decision-making, mitigate risks, and address evolving customer behaviours and regulatory demands. The findings indicate that sentiment analysis enables early detection of market trends, supports more nuanced credit evaluations, and strengthens compliance monitoring by uncovering behavioural patterns and emotional signals across multiple data sources. The study also discusses practical challenges—including data quality, integration issues, and model bias—that must be addressed to realise its full potential. This work contributes to the literature by providing a structured thematic framework and identifying underexplored application areas of sentiment analysis in the FinTech sector. Future research may extend this study by incorporating empirical testing of domain-specific sentiment models.

Keywords: FinTech, Financial Technology, Financial Intelligence, Natural Language Processing, Sentiment Analysis, Strategic Decision-Making

Jel Codes: C81, C88, L86, O32

Öz

Finansal teknoloji (FinTech) sektörü giderek daha fazla veri odaklı stratejileri benimserken, duygu analizi yapılandırılmamış metin verilerinden eyleme dönüştürülebilir içgörüler elde etmek için kritik bir araç olarak öne çıkmaktadır. Bu çalışma, duygu analizinin FinTech alanındaki stratejik uygulamalarını incelemekte; özellikle piyasa tahmini, kredi ve risk değerlendirmesi ile düzenleyici uyum konularındaki rollerine odaklanmaktadır. Akademik çalışmalar üzerine yapılan sistematik tematik analiz temelinde, bu çalışma, finansal kurumların karar alma süreçlerini geliştirmek, riskleri azaltmak ve değişen müşteri davranışları ile düzenleyici gerekliliklere yanıt vermek amacıyla duygu analizinden nasıl yararlandıklarını akademik çalışmalar ışığında sentezlemektedir. Bulgular, duygu analizinin piyasa trendlerinin erken tespiti, daha hassas kredi değerlendirmeleri yapılması ve davranışsal kalıplar ile duygusal sinyallerin analizine dayalı olarak uyum süreçlerinin güçlendirilmesi açısından önemli katkılar sunduğunu ortaya koymaktadır. Çalışma ayrıca, veri kalitesi, sistem entegrasyonu ve model önyargısı gibi uygulamaya yönelik temel zorlukları da ele almakta ve bu teknolojiden en yüksek verimin alınabilmesi için çözülmesi gereken noktaları vurgulamaktadır. Bu araştırma, FinTech ekosisteminde duygu analizine ilişkin yapılandırılmış bir tematik çerçeve sunmakta ve az çalışılmış uygulama alanlarını ortaya koyarak literatüre katkı sağlamaktadır. Gelecek araştırmalar, alanlara özgü duygu analiz modellerinin ampirik olarak test edilmesiyle bu çalışmayı genişletebilir.

Anahtar Kelimeler: FinTech, Finansal Teknoloji, Finansal Zekâ, Doğal Dil İşleme, Duygu Analizi, Stratejik Karar Verme

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Introduction

Financial Technology (FinTech) refers to the integration of innovative digital Technologies (such as mobile applications, blockchain, artificial intelligence, and big data analytics) into financial services to improve efficiency, expand access, and create new value propositions (Murinde, Rizopoulos & Zachariadis, 2022; Bollaert, Lopez-de-Silanes & Schwienbacher, 2021). The rise of FinTech has reshaped the financial sector by leveraging advanced technologies to enhance customer experiences, improve operational efficiency, and unlock new revenue opportunities. As financial services continue to digitalise, institutions face growing demands to meet evolving customer expectations, ensure regulatory compliance, and deliver secure, scalable solutions. To remain competitive in this dynamic environment, financial organisations must foster a culture of continuous innovation and agility in response to shifting market conditions and consumer behaviours.

Moreover, the financial industry increasingly depends on robust data analytics and AI-driven tools to process the vast volumes of information generated each day. These technologies empower organisations to forecast market trends, deliver personalised services, and make data-driven decisions (Campbell, Ansari, & Singh, 2024; Nguyen, Sermpinis, & Stasinakis, 2023; Ashta & Herrmann, 2021; Cao, Yang, & Yu, 2021). Leveraging insights from both structured and unstructured data has become a foundational element of FinTech strategies, enabling firms to proactively navigate emerging opportunities and challenges in a rapidly evolving landscape (Hoang & Wiegratz, 2023; Sahu, Mokhade, & Bokde, 2023).

Within this growing reliance on data and AI, sentiment analysis stands out as a distinctive tool for transforming unstructured textual information into actionable insights, offering unique value for market prediction, risk assessment, and regulatory compliance in the financial technology (FinTech) sector. As a subset of natural language processing (NLP), it examines the emotional tone behind textual data, determining whether sentiments are positive, negative, or neutral (Tan, Lee, & Lim, 2023; Taherdoost & Madanchian, 2023). This capability enables financial institutions to monitor public opinion, detect shifts in market sentiment, and proactively mitigate emerging risks (Rizinski, Peshov, Mishev, Jovanovik, & Trajanov, 2024; Costola, Hinz, Nofer, & Pelizzon, 2023). By leveraging sentiment analysis, FinTech companies can gain timely insights into customer satisfaction, market dynamics, and brand perception. As the FinTech sector continues to grow, sentiment analysis is set to play an increasingly vital role in navigating the complexities of a data-driven financial landscape. Nevertheless, prior research often remains fragmented, highlighting the need for a systematic thematic exploration of sentiment analysis applications across market, risk, and compliance domains.

This study aims to explore the strategic applications of sentiment analysis in the FinTech sector and to assess its transformative role in generating actionable financial insights. The scope of the paper covers key domains where sentiment analysis has been most actively employed, including market prediction and trading, credit and risk assessment, and regulatory compliance. By synthesising findings from academic sources, the study contributes by mapping emerging trends, evaluating methodological approaches, and identifying the critical challenges (such as data quality, integration, and algorithmic bias) that shape adoption. In doing so, it offers both theoretical insights for researchers and practical implications for industry stakeholders. To guide this analysis, the study is structured around the following research questions:

> Research Question (1): In which domains of FinTech is sentiment analysis being applied?
>
> Research Question (2): What methodological approaches are predominantly used in these applications?
>
> Research Question (3): What challenges and limitations shape the effective adoption of sentiment analysis in practice?

The remainder of the paper is organised as follows: it first provides an overview of core sentiment analysis methods and techniques, then outlines the methodological approach and thematic analysis adopted in this study. It subsequently presents the findings across the domains of market, risk, and compliance, followed by a discussion of the implications, limitations, and future research directions, and concludes with key insights and recommendations.

Background

Sentiment analysis, also known as opinion mining, is a subfield of NLP that focuses on extracting, analysing, and categorising emotions, opinions, or attitudes expressed in textual data (Wankhade, Rao & Kulkarni, 2022; Mehta & Pandya, 2020; Yadav & Vishwakarma, 2020). Its primary aim is to determine the sentiment -whether positive, negative, or neutral- within a given piece of text. This analysis is critical for understanding the subjective context of written content, enabling organisations to transform unstructured data into actionable insights. Sentiment analysis has applications across diverse industries, including finance, healthcare, marketing, and politics, where understanding public opinion, customer feedback, or market sentiment is crucial for informed decision-making. By employing sentiment analysis, businesses can improve customer satisfaction, anticipate market trends, and mitigate potential risks, establishing it as a vital tool in today's data-driven landscape.

Sentiment analysis has been explored across several levels to capture varying degrees of granularity and context (Wankhade et al., 2022). Document-level analysis evaluates the sentiment of an entire document, assigning a single polarity to represent the overall sentiment, making it suitable for larger texts, such as articles or studies. Sentence-level analysis breaks down text into individual sentences, determining the sentiment of each, which is helpful for documents containing mixed sentiments. Phrase-level analysis focuses on smaller text units, such as phrases or opinion words, to capture granular sentiments within a document, often used in reviews with multiple aspects. Lastly, aspect-level analysis targets specific attributes or components mentioned in the text, assigning sentiments to each element and aggregating them for an overall sentiment view. These levels cater to various applications, from understanding broad sentiments to gaining detailed insights into specific text elements.

The approaches to sentiment analysis can be broadly categorised into lexicon-based methods, machine learning techniques, hybrid approaches, and emerging methodologies like transfer learning and aspect-based analysis (Wankhade et al., 2022). These techniques underpin the structured process of sentiment analysis, which involves several critical steps to transform raw text into actionable insights (Tan et al., 2023; Lu, Sun, Long, Gao, Feng & Sun, 2023; Al-Qablan, Mohd Noor, Al-Betar & Khader, 2023; Sharma, Ali & Kabir, 2024):

- Data Collection & Scraping: The process of sentiment analysis begins with data collection and scraping, where diverse data sources are identified and gathered based on the analysis objectives. This data can include user-generated content from social media platforms, reviews on e-commerce websites, opinions in news articles, and discussions in specialised forums. The data collection phase often relies on tools such as web scraping software, APIs like the Twitter API, or datasets from platforms like TripAdvisor, Yelp, and Kaggle to ensure a representative and diverse dataset.
- Data Preprocessing: Once data is collected, it undergoes preprocessing to transform raw text into a structured and analysable form. Preprocessing involves cleaning the data by removing noise such as hashtags, mentions, HTML tags, and URLs. Text normalisation ensures consistency by converting the text to lowercase, correcting typos, and standardising formats. Tokenisation breaks the text into smaller units, such as sentences or words, enabling a more granular analysis. These preprocessing steps are essential for reducing data complexity and improving the accuracy of sentiment detection.
- Feature Extraction: After preprocessing, feature extraction and representation are performed to convert text into numerical features suitable for machine learning models. Techniques such as Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) are commonly used to highlight important words and reduce the weight of frequent but less meaningful terms. More advanced methods, like word embeddings such as Word2Vec and GloVe, capture semantic relationships and contextual meanings between words, which provide a richer feature set for sentiment classification.
- Sentiment Analysis: The sentiment classification stage leverages machine learning models to categorise text into predefined sentiment classes, such as positive, negative, or neutral. This step is central to deriving valuable emotional insights from textual data. Advanced sentiment analysis extends beyond basic polarity classification to detect nuanced emotional states, such as happiness, anger, sadness, or surprise, making it highly relevant for applications like customer feedback analysis and behavioural studies. The choice of model depends on the complexity of the task and the available data. For simpler classification tasks, models like logistic regression and decision trees are effective. However, more complex scenarios require sophisticated algorithms, such as neural networks, which excel at identifying intricate patterns in data. Advanced architectures like Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Transformer-based models (e.g., BERT) are particularly well-suited for handling contextual nuances, sequence dependencies, and large-scale textual datasets. Additionally, this stage addresses challenges such as cross-domain and cross-

language sentiment analysis, enabling models to adapt to different domains or languages with minimal retraining. These advancements enhance the accuracy of sentiment analysis and also ensure its adaptability across various applications and datasets.

- Analysis and Visualisation: Finally, the results of sentiment analysis are interpreted and visualised to extract actionable insights. Visualisation techniques such as heatmaps, bar graphs, and line charts play a crucial role in enabling stakeholders to monitor sentiment trends, compare sentiments across various categories, and analyse sentiment distributions geographically. These visual tools ensure that the outcomes of sentiment analysis are both accessible and comprehensible. They empower organisations to make informed decisions and respond effectively to the insights generated.

Figure 1 presents an example of a sentiment analysis workflow tailored to financial applications. The process begins with identifying and collecting data from diverse sources, including social media posts, financial news articles, customer reviews, stock market reports, and annual reports. These sources ensure a well-rounded dataset that captures a wide range of public sentiment and market dynamics, forming the foundation for accurate and meaningful sentiment analysis.

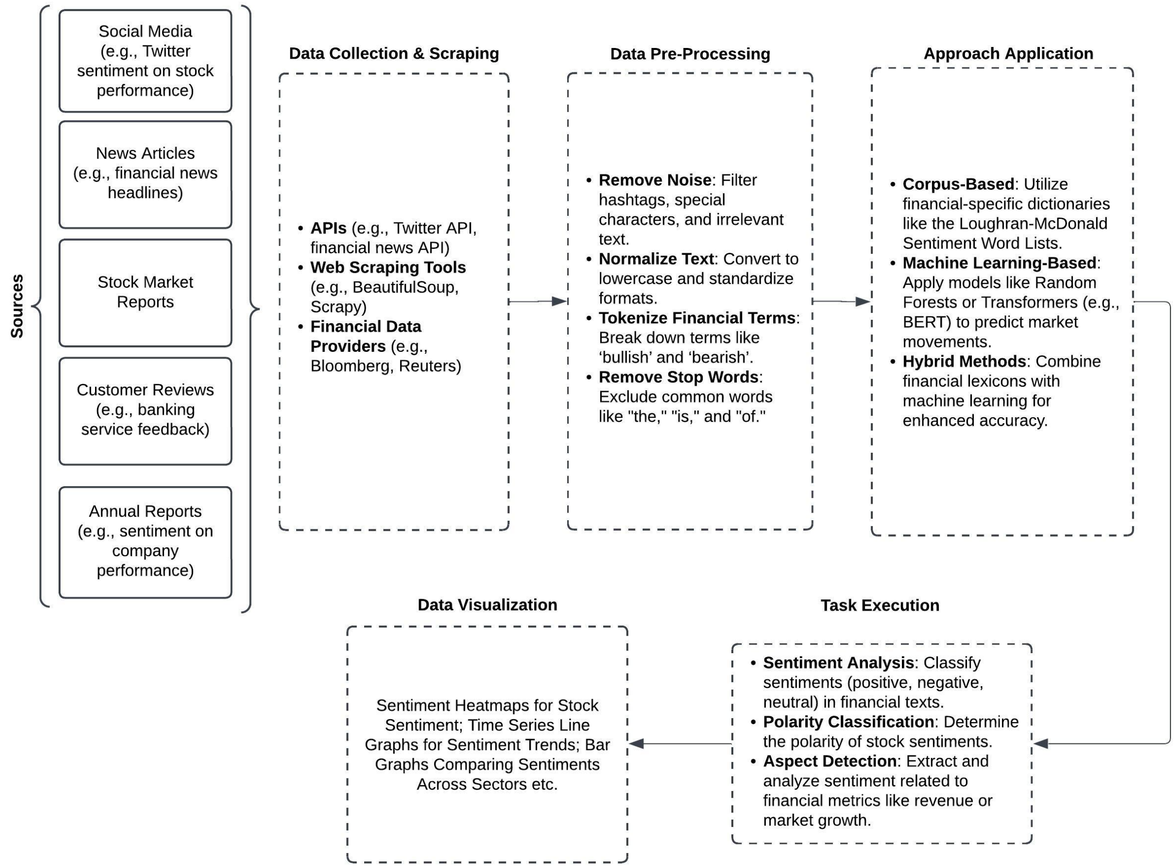

Figure 1: An Example of a Sentiment Analysis Workflow for Financial Applications

Source: Author's own work

Methodology

This study adopts a qualitative, literature-driven approach to examine the applications of sentiment analysis in the FinTech sector. The research design was intended to capture both theoretical perspectives and practical implementations, thereby providing a comprehensive view of the field. Relevant sources were collected from academic databases, including Scopus, Web of Science, IEEE Xplore, and Google Scholar. The focus was on works published between 2010 and 2024, complemented by seminal earlier contributions where necessary to establish conceptual foundations. Keyword combinations included "FinTech and NLP", "sentiment analysis in finance", "AI in financial services", and "financial text analytics", ensuring the retrieval of a broad yet relevant body of literature.

The screening process applied explicit inclusion and exclusion criteria to refine the dataset. Only English-language, peer-reviewed studies that directly addressed sentiment analysis in FinTech contexts were retained. Purely technical NLP studies without financial relevance and non-academic sources lacking methodological rigour were excluded. This process initially yielded 71 records, which, after duplicate removal and title/abstract screening, resulted in 58 studies being selected for full-text review. This approach ensured both comprehensiveness and analytical focus.

To interpret and synthesise the findings, a thematic analysis was conducted (Gephart et al., 2018; Clarke & Braun, 2014). Through iterative reading, coding, and categorisation, recurrent patterns were identified and grouped into four major application domains: (1) market prediction and trading strategies, (2) credit and risk assessment, (3) customer engagement and service enhancement, and (4) regulatory compliance. Themes were iteratively reviewed and cross-checked to ensure consistency and reliability of coding. This method provided the flexibility to accommodate diverse types of literature, enabling the identification of technological trends, implementation challenges, and research gaps. The synthesis provides insights into current practices and future directions of sentiment analysis in the evolving FinTech landscape.

Findings and discussion

The findings of this study are structured around four major thematic domains that emerged through a comprehensive review and qualitative synthesis of the literature. Applications of sentiment analysis in FinTech have significantly transformed how financial institutions understand customer behaviour, respond to market dynamics, and anticipate economic shifts. These advancements have enabled the development of data-driven strategies that enhance decision-making and operational efficiency (Bredice, Formisano, Kullafi, and Palma, 2025; Ranjan, Sharma, and Kumar, 2025; Huang, Zavareh, & Mustafa, 2023; Faccia, McDonald, and George, 2023; Das & Singh, 2023).

These findings also provide answers to the research questions outlined in the introduction. First, they demonstrate how sentiment analysis is being strategically applied across different FinTech domains, ranging from trading to compliance. In doing so, the results are categorised into four key areas of application: (1) market and trading strategies, (2) credit and risk assessment, (3) customer service and support, and (4) regulatory compliance and monitoring. Second, they highlight the key benefits and limitations of these applications, particularly in enhancing decision-making, risk assessment, and customer engagement. Finally, they point to emerging trends and future directions, underscoring both the opportunities and challenges that shape the evolving role of sentiment analysis in FinTech. Each of these domains reflects a unique set of strategic functions where sentiment analysis contributes to performance improvement, risk mitigation, and competitive advantage in the FinTech landscape.

Key Category 1: Market and Trading Strategies

FinTech companies are increasingly leveraging sentiment analysis to enhance market and trading strategies, rather than relying on traditional data analysis approaches. By incorporating real-time sentiment analysis from diverse textual sources, traders and analysts can gain immediate insights into market dynamics and investor emotions. This capability enriches market intelligence and also enables the anticipation of price fluctuations before they materialise (Delgadillo, Kinyua, & Mutigwe, 2024; Karanikola, Davrazos, Liapis, & Kotsiantis, 2023).

A wide range of data sources underpins sentiment analysis, each offering unique insights that collectively allow firms to monitor public reactions, gauge investor sentiment, and identify emerging trends. Financial news articles serve as critical inputs, providing updates on market developments, policy announcements, and corporate actions that help firms assess how these events might influence stock prices and trading behaviours. Investor blogs and analyst reports add a layer of expertise, offering specialised insights into industries, companies, or financial instruments through detailed analyses and expert opinions. They enhance the depth and accuracy of sentiment insights.

Social media platforms are particularly valuable for real-time sentiment tracking due to their immediacy and broad reach. Twitter allows firms to monitor public sentiment around breaking financial news, corporate updates, or policy changes in real time. LinkedIn adds a professional perspective, offering industry-specific insights and expert opinions that signal potential shifts in market sentiment. Reddit, through active financial communities like r/WallStreetBets, captures grassroots sentiment and collective investor behaviours, which have shown the potential to drive significant market movements. These diverse sources collectively enable FinTech companies to refine their trading strategies and stay ahead in volatile market conditions.

Some innovative applications of sentiment analysis in market and trading strategies are as follows (Bredice et al., 2025; Ranjan et al., 2025; Yang, Cheng, Li, Wang & Wei, 2024; Praghaadeesh, Maniappan

& Doss, 2024; Kim, Ryu & Yu, 2022; Colianni, Rosales & Signorotti, 2015; Rao & Srivastava, 2014; Zhang & Skiena, 2010):

- Algorithmic Trading: Automated trading systems integrate sentiment scores derived from news, financial analyses and social media, to execute trades with unmatched speed and precision. For instance, a positive sentiment surge following a policy announcement could trigger immediate stock purchases in the impacted sector, allowing firms to capitalise on favourable price movements.
- Risk Management: Sentiment indicators help traders assess market mood -bullish or bearish- and adjust risk exposure accordingly. For example, widespread negative sentiment might prompt shifts to safer asset classes or increased cash holdings, reducing potential losses.
- Market Trend Prediction: By tracking sentiment changes over time, investment firms can anticipate market movements before they are reflected in prices. This enables them to position portfolios advantageously, whether by investing in sectors with positive sentiment or avoiding those with declining sentiment.
- Portfolio Management: Portfolio managers utilise sentiment analysis to optimise asset allocation. Understanding sentiment trends towards specific sectors or stocks enables managers to adjust portfolios proactively, improving alignment with potential market movements and enhancing performance.
- Sentiment Index Creation: Some firms develop proprietary sentiment indices by aggregating sentiment data from multiple sources into a single measurable metric. These indices serve as a benchmark for evaluating the health of a market or sector, enabling the comparison of individual stock or portfolio performance against market averages.

For example, during a significant corporate merger announcement, an investment firm utilised sentiment analysis to assess public and market reactions across various regions and demographics. By identifying trends in positive and negative sentiments, the firm strategically adjusted its investment positions in the merging companies, effectively capitalising on short-term market volatility to realise substantial gains.

Integrating sentiment analysis into market and trading strategies enables FinTech firms to leverage powerful tools that enhance decision-making, optimise risk management, and improve market predictions. As financial markets continue to evolve with advancements in technology, sentiment analysis is poised to become an essential component of sophisticated trading operations. It empowers firms to develop strategies that are closely aligned with real-time market sentiments and investor behaviours, and ensures a competitive edge in a rapidly changing financial landscape.

Key Category 2: Credit and Risk Assessment

FinTech companies are increasingly using sentiment analysis to complement and enhance traditional credit risk assessment methods. By integrating behavioural finance principles, this approach offers a more comprehensive view of a borrower's financial health. Textual data from customer reviews, forum discussions, and social media posts are analysed to uncover attitudes and emotional signals, which can reveal patterns in financial behaviour and potential creditworthiness beyond conventional metrics. Such insights enable more nuanced evaluations, thereby improving predictive accuracy and supporting risk mitigation strategies (Todd, Bowden, and Moshfeghi, 2024; Mienye, Jere, Obaido, Mienye, & Aruleba, 2024; Nazareth & Reddy, 2023).

Sentiment analysis relies on a variety of data sources to provide a nuanced understanding of consumer behaviours and attitudes toward finance. Customer reviews serve as a valuable resource, which offer direct feedback on financial products and services. Positive reviews may indicate trust and satisfaction, while negative feedback can highlight frustrations with service quality or product features, shedding light on customer expectations. Similarly, financial forums allow users to discuss topics like debt, spending habits, and market conditions, providing insights into collective financial behaviours and individual attitudes. These discussions can help FinTech firms identify behavioural trends, such as conservative spending during economic uncertainty or riskier behaviour during bullish markets.

Social media platforms like Twitter and Facebook add another layer of real-time sentiment analysis. They capture immediate reactions to financial events, such as policy announcements, market shifts, or changes in product offerings. For example, a spike in negative tweets about a bank's newly introduced fees can prompt the institution to address customer concerns quickly. Likewise, celebratory posts about milestones, such as debt repayment or investment success, reveal consumer confidence and positive financial behaviours.

By synthesising insights from these diverse sources, FinTech companies can refine their credit risk assessments, develop targeted financial products, and enhance customer engagement strategies. This integration of sentiment analysis into risk assessment frameworks allows for a more dynamic and responsive approach, aligning financial services with the evolving needs and behaviours of customers.

Some innovative applications of sentiment analysis in credit risk assessment are as follows (Bredice et al., 2025; Ranjan et al., 2025; Bello, 2023; Kim et al., 2022; Bhatore, Mohan & Reddy, 2020; Wang, Qi, Fu & Liu, 2016; Zhang, Xu, Zhu & Zhang, 2015):

- Enhanced Credit Scoring: Traditional credit scoring models predominantly rely on historical financial data, such as payment history and credit utilisation rates. Sentiment analysis adds a behavioural dimension to these models by examining online discussions and consumer feedback about financial experiences and attitudes. This dynamic component allows lenders to predict potential financial behaviours, offering a more comprehensive assessment of creditworthiness. For example, borrowers displaying consistent positive sentiment in discussions about financial responsibility may be deemed lower risk, while those with negative attitudes towards debt management may warrant closer scrutiny.
- Early Warning Signs of Financial Distress: Sentiment analysis is highly effective at detecting early indicators of financial distress. Shifts in consumer sentiment—such as increasing negativity in forum discussions about personal finances or economic outlook—can signal potential challenges before they are reflected in traditional credit metrics. Financial institutions can leverage these insights to proactively engage with customers, offering tailored solutions to mitigate risks and support borrowers in managing their obligations.
- Customised Financial Products: By analysing customer sentiment, financial institutions can develop products that align with specific needs and preferences. For instance, positive sentiments towards investment opportunities might suggest demand for higher-risk, higher-reward financial products. Conversely, cautious or negative sentiments could indicate a preference for conservative options, such as low-risk savings accounts or fixed-income instruments. Tailoring offerings based on sentiment ensures higher customer satisfaction and engagement.
- Behavioural Risk Profiling: Sentiment analysis enables a deeper understanding of behavioural risk factors that complement traditional credit assessments. For example, analysing an individual's sentiment towards financial planning or debt management provides insights into their long-term financial habits and reliability. This profiling helps lenders differentiate between borrowers with similar credit scores but varying risk profiles.
- Strategic Customer Engagement: Sentiment analysis facilitates targeted communication with borrowers. For example, financial institutions can use sentiment trends to identify customers who may benefit from financial counselling or restructuring options. Positive engagement during challenging periods fosters trust and reduces default risks, improving overall customer relationships.

A practical example highlights a credit card company that leveraged sentiment analysis to monitor social media and customer feedback about its card fees. The company identified a correlation between rising negative sentiment and an increase in late payments. In response, it strategically adjusted its fee structures and communicated the changes effectively to customers. This proactive approach mitigated dissatisfaction, reduced default rates and enhanced overall customer engagement.

Incorporating sentiment analysis into credit risk assessment allows FinTech companies to develop more dynamic and nuanced evaluations of financial behaviour. By identifying potential risks early, lenders can customise financial solutions to meet individual customer needs while strengthening relationships. This approach enhances risk management and customer satisfaction, and provides a competitive edge in an evolving economic landscape.

Key Category 3: Customer Service and Support

The integration of sentiment analysis in customer service has transformed and continues to reshape how financial technology companies interact with their clients. By detecting and responding to emotions expressed through digital interactions— such as emails, chatbots, or social media —firms can deliver personalised services that better address individual needs and strengthen overall satisfaction

(Pandow, 2024; Du, Xing, Mao and Cambria, 2024; Rodríguez-Ibánez, Casánez-Ventura, Castejón-Mateos and Cuenca-Jiménez, 2023; Huang et al., 2023). Beyond resolving customer issues more effectively, this approach enriches the overall user experience by ensuring that responses are timely, contextually appropriate, and aligned with customer expectations. In doing so, it strengthens customer relationships and fosters long-term loyalty and trust.

The integration of sentiment analysis in customer service is transforming how financial technology companies interact with their clients. By analysing and responding to customer emotions expressed through digital interactions, companies can deliver personalised services that cater to individual needs and enhance overall customer satisfaction (Pandow, 2024; Du et al., 2024; Rodríguez-Ibánez et al., 2023; Huang et al., 2023). This approach improves the resolution of customer issues and enriches the overall experience by ensuring that responses are both timely and contextually appropriate.

To effectively understand customer emotions, sentiment analysis leverages a variety of data sources. Email communications often contain direct feedback or concerns, where the tone and urgency of the sender are critical cues for prioritising responses. Social media platforms, such as Twitter, Facebook, and LinkedIn, provide real-time access to public sentiment, capturing immediate reactions and overarching trends regarding products or services. Similarly, customer reviews and feedback, collected via surveys or review platforms, offer valuable insights into satisfaction levels and service quality. These data points help identify recurring themes and highlight areas needing improvement.

Additionally, live chat sessions enable real-time sentiment analysis, allowing customer service agents to adjust their approach in response to customer feedback. By identifying emotional cues during conversations, agents can respond empathetically to dissatisfaction or adopt a more assertive approach when necessary. Together, these diverse data sources empower FinTech companies to refine their customer service operations, ensuring that interactions are both efficient and emotionally resonant, thereby fostering deeper customer loyalty and engagement.

Sentiment analysis is transforming customer service by enabling more nuanced and responsive interactions (Singh, Banik, Roy & Pandit, 2025; Palos-Sanchez, Chang-Tam & Folgado-Fernández, 2025; Rane, Choudhary & Rane, 2024; George & Baskar, 2024; Udeh, Amajuoyi, Adeusi & Scott, 2024; Saxena & Muneeb, 2024; Cao, 2022). Some key applications include:

- Personalisation of Customer Interactions: FinTech firms use sentiment analysis to tailor customer interactions. For example, suppose a customer expresses dissatisfaction in a review. In that case, service agents can reach out with tailored solutions to address specific concerns, potentially converting a negative experience into a positive one. Personalised interactions foster stronger relationships and enhance customer loyalty.
- Real-Time Response and Problem Resolution: By identifying negative sentiments in real-time, such as during live chat sessions, customer service teams can immediately escalate issues to specialised personnel. This proactive approach improves resolution times and prevents customer churn. For instance, if a customer expresses frustration about a delayed transaction, sentiment analysis can trigger instant support or intervention from higher-level teams, ensuring swift resolution.
- Enhanced Customer Journey Mapping: Sentiment analysis helps companies map the emotional journey of their customers across various service touchpoints. Understanding when and where customers feel pleased, confused, or upset allows businesses to make targeted improvements. For instance, frequent negative sentiments at the payment gateway could prompt simplification of this process, reducing friction and enhancing the customer experience.

Incorporating sentiment analysis into customer service operations enables FinTech companies to achieve exceptional levels of personalisation and operational efficiency. By adapting dynamically to emotional feedback, businesses can go beyond meeting customer expectations to consistently exceed them, which enables greater loyalty and long-term satisfaction. As technology advances, sentiment analysis will play an increasingly pivotal role in customer service.

Key Category 4: Regulatory Compliance and Monitoring

In the financial services industry, regulatory compliance is paramount, and sentiment analysis has become a powerful tool for monitoring adherence to evolving requirements (Faccia et al., 2023; Fritz & Tows, 2018). By analysing nuances in communication and detecting emotional cues, financial institutions can proactively identify potential compliance risks before they escalate. This capability reduces the likelihood of regulatory breaches and associated penalties, while also strengthening transparency and accountability in financial reporting. Looking ahead, the integration of sentiment analysis with advanced monitoring systems is expected to further support regulators and firms in maintaining trust, integrity, and stability across the financial ecosystem.

Effective compliance monitoring through sentiment analysis leverages multiple data sources, each providing distinct insights to ensure regulatory adherence. Employee communications, such as emails and instant messages, are critical for identifying potential compliance issues. By analysing the tone and content of these exchanges, institutions can detect problematic behaviours, such as aggressive sales tactics or misleading statements, before they escalate into regulatory breaches. Proactive monitoring of internal communications fosters a culture of compliance and helps prevent non-compliant activities from slipping through unnoticed.

Customer feedback is another essential source for regulatory compliance. Feedback collected via surveys, reviews, or complaints provides insights into whether financial services meet regulatory standards and customer expectations. Sentiment analysis of this feedback allows institutions to identify trends and swiftly address compliance-related issues, such as product misrepresentation or dissatisfaction with service delivery. This ensures better alignment with regulatory standards while enhancing customer trust and satisfaction.

Public and social media statements represent a third vital source. Analysing the statements made by company representatives on platforms like Twitter, Facebook, or LinkedIn can help safeguard against the dissemination of misleading information. Sentiment analysis flags comments that deviate from regulatory guidelines, enabling companies to mitigate potential reputational or legal risks. Additionally, monitoring public sentiment offers an external perspective on the company's adherence to compliance standards and its management of public perception, helping institutions stay aligned with both regulatory requirements and stakeholder expectations.

Sentiment analysis serves as a crucial tool in enhancing regulatory compliance through several key applications (Palos-Sanchez et al., 2025; Du et al., 2024; Faccia et al., 2023; Das & Singh, 2023; Cao, 2022; Fritz & Tows, 2018; Sun & Vasarhelyi, 2018). Some key applications are as follows:

- Monitoring Communications for Compliance: Financial institutions employ sentiment analysis tools to continuously monitor the tone and content of internal and external communications. For instance, if aggressive sales tactics are detected in employee emails or chat messages, compliance officers can intervene to ensure alignment with consumer protection laws.
- Detecting Non-Compliant Behaviour: Sentiment analysis helps identify behaviours or statements that may indicate non-compliance. For example, overly optimistic sentiments in financial forecasts or promotional materials may trigger a compliance review to verify the accuracy of claims, preventing potential misrepresentation.
- Enhancing Reporting and Auditing Processes: By analysing the sentiment within financial documentation, institutions can identify areas that require closer scrutiny during audits. For example, negative or overly cautious sentiments in reports may indicate underlying issues that need to be addressed, thereby improving the accuracy and reliability of audit outcomes.
- Training and Development: Sentiment analysis of feedback from compliance training programs helps assess their effectiveness. Negative sentiments in trainee feedback might highlight gaps in understanding or areas where the training content needs refinement, leading to more comprehensive and impactful compliance education.

The integration of sentiment analysis into regulatory compliance and monitoring processes enables financial institutions to adopt a proactive approach to managing compliance risks. By enabling early detection of potential issues and enhancing the agility of compliance frameworks, sentiment analysis serves as a critical tool in preventing regulatory breaches. This forward-looking approach not only safeguards institutions from legal and regulatory consequences but also strengthens trust and credibility among customers and regulators. Ultimately, sentiment analysis fosters a resilient culture of compliance, enabling institutions to navigate an increasingly complex and dynamic financial landscape with confidence and agility.

Challenges of sentiment analysis for financial applications

While sentiment analysis holds significant promise for financial applications, its implementation in FinTech faces several challenges and limitations that must be addressed to unlock its full potential and ensure accurate, actionable insights (Sai et al., 2025; Raghunathan & Saravanakumar, 2023; Cao, 2022; Wankhade et al., 2022; Rizinski et al., 2022).

A significant challenge in sentiment analysis is data quality and management. Financial institutions manage large datasets from diverse sources, including social media, customer reviews, and internal communications. Ensuring data accuracy, relevance, and consistency is crucial, as low-quality data can lead to unreliable sentiment detection and flawed conclusions. Furthermore, unstructured data, such as text and audio, requires sophisticated tools and substantial computational resources for effective processing (Whang, Roh, Song & Lee, 2023; Dwivedi, Wójcik & Vemareddyb, 2021).

Another critical concern involves privacy and ethics. The collection and analysis of sensitive personal data in sentiment analysis raises privacy and ethical considerations. For instance, analysing employee communications or customer feedback can inadvertently infringe on individual privacy if not managed carefully. Financial institutions must ensure compliance with privacy regulations, such as the GDPR, and implement robust safeguards to protect user data. Ethical issues, including transparency in data usage and avoiding biases in sentiment analysis, are also critical to maintaining trust and fairness (Sai et al., 2025; Fazil, Hakimi & Shahidzay, 2023).

A further challenge lies in integrating sentiment analysis with existing financial systems. Many legacy systems used by financial institutions lack the flexibility to accommodate advanced sentiment analysis models. Successful integration requires technical expertise, robust infrastructure, and coordination between IT and business units to ensure that sentiment analysis outputs are seamlessly incorporated into decision-making processes (Khan, Khan, Nazir, Albahooth & Arif, 2024; Du et al., 2023; Cao, 2022).

A further limitation concerns bias and interpretation errors in sentiment analysis models. Systems that rely on generic or imbalanced datasets frequently fail to capture the subtleties of financial language, such as technical jargon, regulatory discourse, or market-specific expressions. This disconnect often results in skewed or misleading outputs, particularly when tools trained in non-financial domains are applied directly to financial decision-making contexts. Moreover, oversimplified interpretations of sentiment scores, such as treating all positive signals as favourable for markets or all negative ones as unfavourable, risk-distorting insights and leading to misguided investment strategies. To overcome these shortcomings, models must be refined and adapted to meet the financial sector's requirements, algorithmic bias needs to be systematically mitigated, and outputs should always be contextualised within domain-specific knowledge. Without such measures, sentiment analysis risks amplifying existing biases and generating unreliable or even harmful conclusions (Raghunathan & Saravanakumar, 2023; Fazil et al., 2023; Rizinski et al., 2022).

Addressing these challenges is crucial to maximising the potential of sentiment analysis in FinTech, enabling institutions to effectively leverage this transformative tool while maintaining trust, compliance, and operational excellence.

Limitations of the study

This study is limited by its literature-based methodology, which relies on secondary sources and does not include primary empirical data such as interviews or case studies. As a result, the findings may not fully reflect real-world implementations or context-specific practices in the FinTech sector. The interpretive nature of the thematic categorisation introduces the possibility of researcher bias, and the exclusion of non-English sources may also limit the global scope of analysis. Additionally, given the rapid evolution of sentiment analysis and FinTech technologies, the relevance of the findings may diminish over time without continual updates through empirical research. Future studies incorporating primary data collection and cross-lingual sources will be essential to validate and expand upon these insights, thereby ensuring their continued relevance in the FinTech landscape.

Conclusion

Sentiment analysis has emerged as a transformative technology, reshaping the way financial institutions navigate the complexities of a dynamic and data-intensive industry. This study examined the transformative impact of sentiment analysis in the FinTech sector, highlighting its applications across four key domains: market and trading strategies, credit and risk assessment, customer service and support, and regulatory compliance and monitoring. By leveraging advanced natural language processing techniques and integrating insights from diverse data sources such as financial news, social media, and customer reviews, sentiment analysis enhances decision-making, streamlines risk management, and fosters personalised customer engagement. The study also highlighted the challenges of implementing sentiment analysis, including data quality issues, biases, and system integration problems, underscoring the importance of refining models and processes for financial contexts. The use cases and applications discussed demonstrate that sentiment analysis has become a core component of FinTech, enabling firms to remain competitive in a data-driven environment.

Sentiment analysis is expected to grow and adapt to new trends, driven by AI and data innovations. Future directions include:

- Integrating Multimodal Analysis: Combining textual data with audio, visual, and behavioural inputs to achieve a richer and more comprehensive understanding of sentiment, especially valuable for applications such as fraud detection and customer behaviour analysis.
- Advancing Real-Time Sentiment Analytics: Developing enhanced algorithms that enable instant processing of high-velocity data streams, such as live financial news and social media feeds, to support time-sensitive decision-making in trading and market analysis.
- Focusing on Explainable AI (XAI): Ensuring greater transparency and interpretability in sentiment models to meet regulatory requirements and build stakeholder trust, which is critical for financial applications with significant economic and societal impacts.
- Developing Domain-Specific Pretrained Models: Creating customised pretrained models for FinTech to improve the accuracy and relevance of sentiment analysis, especially in contexts that require precise interpretation of financial jargon.
- Integrating Behavioural Profiling: Leveraging sentiment analysis to enhance behavioural profiling, enabling financial institutions to predict customer actions more accurately. This trend will facilitate personalised financial solutions, improve risk assessments, and detect fraud by identifying deviations in typical behaviours.
- Integrating with Blockchain and Smart Contracts: Utilising sentiment analysis to automate decision-making in blockchain-based systems, such as adjusting terms in smart contracts based on market sentiment trends.
- Enhancing Visualisation Tools: Developing advanced interactive dashboards and visualisation tools to make sentiment trends, anomalies, and insights more accessible and actionable for decision-makers, empowering organisations to leverage sentiment analysis effectively.

These advancements underscore the increasing significance of sentiment analysis in revolutionising FinTech operations. In addressing the research questions posed in the introduction, the study demonstrates how sentiment analysis is applied across FinTech domains, outlines its benefits and limitations, and identifies future trends that will shape its role. This research contributes to the literature by offering a structured thematic framework and highlighting underexplored application areas, while also providing practical insights for industry adoption. Together, these contributions ensure that sentiment analysis remains a central and evolving tool in shaping the future of financial services.

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