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Sentiment analysis of sales transactions for customer behavior and revenue prediction

Rahamath Mohamed Razikh Ulla *

Capitol Technology University, Maryland, USA.

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Abstract

The development of sentiment analysis and sales transaction analytics is a major breakthrough in customer intelligence and sales prediction using data. Although the conventional revenue prediction models depend on structured transactional variables, where price, quantity, frequency and promotional activity play the key role, emerging knowledge remains that the unstructured customer generated text offers complementary behavioral variables that improve the predictive outcome. Recent developments in deep learning, multimodal learning models, and interpretable machine learning have made it possible to systematically incorporate the synthesized and unstructured data streams into coherent predictive models. This review has looked at methodological advances, modelling approaches and experimental results on sentiment-enhanced customer behavior modelling and revenue prediction. The discussion has identified the contribution of sentiment polarity, emotional intensity, and contextual embeddings to the churn prediction, repeat purchase probability and multi-horizon revenue forecasting. It was found that the main issues were to integrate the data, provide interpretability of models, reduce bias, achieve scalability, and cross-domain generalization. Another key point made in the review is that explainable AI frameworks are necessary in order to provide managerial trust and regulatory adherence in high-stakes decisions. The results suggest that sentiment enhanced forecasting models are incremental predictors when they are appropriately calibrated and tested. Nevertheless, the next generation of studies should concern the standardization of methods, the multimodal alignment, and the ethical issues to allow the application of such devices in commercial systems.

Keywords*:* Business analytics; Customer behavior prediction; Explainable AI; Multimodal learning; Natural language processing; Predictive modelling

1. Introduction

The fast-paced digitalization of the business has produced unprecedented amounts of transactional and behavioral data. A sales transaction no longer exists in the form of a numbered list of the quantities, prices, and time, but rather it comes with unstructured information in the form of customer reviews, feedback forms, social media comments and support interactions. The integration of structured transactional data with unstructured textual data has created new opportunities of advanced analytics, and especially with the methods of sentiment analysis, based on artificial intelligence (AI) and natural language processing (NLP) [1], [2].

Sentiment analysis can be described as the process of computationally identifying and classifying opinions in a text but has dramatically changed with the advancement of machine learning and deep learning models [3], [4]. The initial lexicon-based models have been supplanted and/or supplemented by contextual semantics learning algorithms and transformer-based models that can learn contextual semantics at scale [5], [6]. Similarly, sales and revenue prediction have advanced beyond classical statistical models to hybrid frameworks that incorporate machine learning, time-series

* Corresponding author: Rahamath Mohamed Razikh Ulla

modelling, and big data analytics [7], [8]. Sentiment analysis integrated with sales transaction data is a critical point of interface of these trends, as it allows more detailed modelling of customer behavior and revenue dynamics.

This is an important issue in the context of AI-based business intelligence and data science. Widespread use of data-driven decision-making is increasingly prevalent in organizations to promote better customer experience, better pricing techniques, inventory management, and better revenue forecasts [9]. Customer sentiment has been shown to have an impact on purchasing behavior, brand loyalty, and churn behavior and therefore is a valuable indicator of the future revenue stream [10], [11]. Even very slight increases in predictive accuracy in the highly competitive digital marketplaces can be converted into large financial gains. In turn, sentiment signal integration with transactional metrics is consistent with the current development of AI-related technologies, big data infrastructure systems, and cloud-based analytical solutions [12].

However, despite the increased attention, there are a number of issues that remain in the effective application of sentiment analysis in predicting customer behavior and revenue. To start with, the heterogeneity of data sources, i.e. structured sales records, messy, unstructured textual inputs, etc., is a source of significant challenges in data integration and preprocessing [13]. Second, sentiment polarity in itself might be inadequate to capture subtle emotional nuances, contextual sarcasm or domain-specific language, which may result in misclassification and lower predictive accuracy [14]. Third, the current literature concentrates on isolated sentiment analysis or the conventional sales forecasting framework, although little emphasis has been placed on the integration of the two modalities, and unified frameworks have not been systematically investigated [15]. Moreover, the problems of model interpretability, training data bias, scalability, and cross-domain generalization are still not well examined [16], [17].

The next potential gap is that the comparative analysis of the classical statistical approaches, traditional machine learning models, and novel deep learning structures has been under-evaluated in the particular setting of revenue prediction that is reinforced by sentiment signals. Although transformer-based models such as BERT, as well as its variations, prove to be highly useful in text classification tasks [6], the evidence on the incremental value of its use in conjunction with transactional features to predict revenue is inconclusive. Also, the ethics of customer data privacy and responsible implementation of AI in this area have not always been thoroughly studied [18].

A review is therefore necessary and timely in light of these research gaps. The current review attempts to critically review the existing body of literature regarding sentiment analysis of sales transactions to model customer behavior and predict revenue. It breaks down methodological plans, data combination strategies, feature engineering plans, model design, validation frameworks, and performance measures. Emerging trends such as multimodal learning, explainable AI and real-time analytics are also discussed critically.

This paper is organized into a systematic summary of (i) the conceptual basis in the field of sentiment analysis and sales analytics, (ii) methodological innovations in the field of textual sentiment analysis and transactional data, (iii) comparative studies of predictive modelling techniques, (iv) practical and industry case studies, and (v) challenges and ethical issues and future research. This review aims at unifying the scattered literature, highlighting gaps in the knowledge, and providing a consistent framework for future research related to how AI can be used to predict customer behavior and revenue.

2. Literature Review

Table 1 Summary of key research

Focus	Findings (key results and conclusions)	Ref.
Quantifying how online review valence affects relative product sales across platforms	Review valence is associated with relative sales differences across retailers; negative signals can have asymmetric influence compared with positive signals, indicating that text-based WOM contains economically meaningful demand information.	[19]
Modelling how word-of-mouth dynamics relate to revenue outcomes (movie box office)	WOM volume and its temporal dynamics help explain box office revenue patterns, highlighting that consumer conversation intensity and timing are predictive signals for revenue trajectories.	[20]
Improving sales forecasts by adding online review metrics to	Adding online review signals to benchmark forecasting models improves forecasting accuracy beyond prerelease marketing and expert reviews;	[21]

baseline forecasting models (motion pictures)	consumer-generated signals provide incremental predictive power for sales/revenue.	
Disentangling “persuasive” vs “awareness” effects of online reviews on sales (movies)	The relationships between review volume and associated attention cues are found to be strong regarding sales and a modelling of review endogeneity alters inference regarding its effects, in that review and sales change with time.	[22]
Linking review characteristics (including reviewer identity disclosure) to sales outcomes (electronic markets)	Review valence and volume relate to sales, and reviewer/source characteristics (e.g., identity disclosure) can strengthen economic impact, indicating that “who says it” can matter alongside “what is said.”	[23]
Predicting sales using online chatter from social media/blog-like sources (music industry)	Pre- and post-release chatter measures improve sales prediction for albums; online conversation contains leading indicators that complement traditional predictors around launch windows.	[24]
Identifying when online reviews matter most for sales (product + consumer moderators)	The effect of reviews on sales depends on product popularity and consumer characteristics; online reviews are more likely to influence with products that are not so popular and when consumer segments are more digitally active.	[25]
Capturing social dynamics in rating environments and downstream sales effects	Ratings have a social influence process; the modelling of rating change can be used to predict the impact of the rating environment on the future ratings and the sales of products, and thus, dynamic eWOM representations are favoured over static ones.	[26]
Mining review text to estimate economic impact of product features and review content	Review text mining can extract the economic utility of product attributes and measure the relationship between the content of reviews and demand performance, which justifies feature-based feature-level sentiment-as-preference modelling.	[27]
Decomposing and contextualizing online review effects on consumer choice (implications for sales)	Other review distribution characteristics (e.g., variance/volume) can moderate review valence effects and can lead to brand independent effects in choice, which suggests that review-based sentiment indications can redefine purchase decision driving forces that would be predictive of revenues.	[28]

3. Methodology

The proposed framework is a multimodal analytical pipeline that combines structured transactional data with unstructured sentiment data in the proposed framework. This structure aligns with current business intelligence architectures that integrate big data processing, NLP and predictive analytics [29], [30].

Such a hierarchical design incorporates recent developments in multimodal learning and interpretable forecasting systems [30], [33]. The suggested system architecture is designed as six interconnected layers. Layer 1 includes data sources: structured data such as price, quantity, time, promotional activity and customer identifiers (or any other structured data about sales transactions), and unstructured customer-generated texts such as reviews, ratings, chats, and social media comments. Layer 2 is concerned with data engineering processes such as ETL and aggregation algorithms, text preprocessing algorithms like tokenization and normalization, feature engineering algorithms that model RFM metrics and textual embeddings. Layer 3 involves sentiment and feature extraction through a combination of lexicon-based and machine learning-based sentiment scoring methods [31], contextual embeddings created using transformer-based NLP models [32], and behavioral data, including purchase frequency, recency, and basket value. Layer 4 combines both structured and unstructured features in multimodal fusion strategies, including early and late fusion mechanisms, attention-based weighting, and multi-task learning architecture. Layer 5 contains prediction modules that produce customer behavior prediction outputs (such as churn risk, repeat purchase likelihood and purchase propensity) and revenue forecasting in short-term and multi-horizon context. Lastly, layer 6 implements explainability and monitoring mechanisms, and applies model interpretability methods like SHAP and LIME [33], [34], as well as bias detection and data drift monitors to ensure robustness, transparency and responsible deployment.

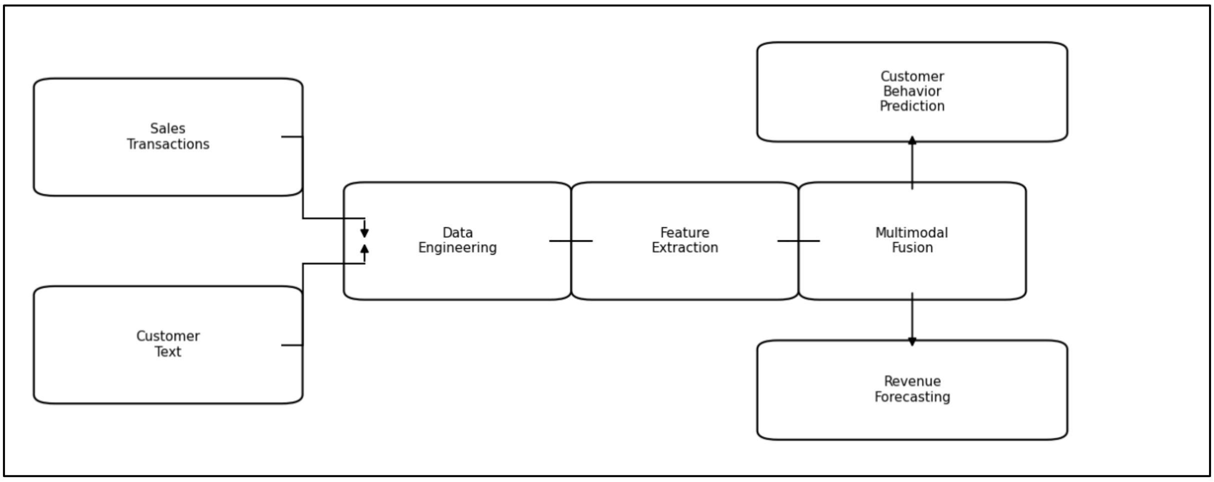

Figure 1 Block diagram: End-to-end pipeline

The theoretical model combines the sentiment theory, customer experience modelling and predictive analytics. It is based on electronic word-of-mouth studies, theory of customer value, and interpretable AI models [29], [31], [33]. In the proposed theoretical framework, we shall have two major groups of independent variables, namely, transaction and sentiment signals. Structured behavioral and economic signals are transaction signals, and they encompass indicators like Recency-Frequency-Monetary (RFM) measures, price elasticity indicators, and basket size indicators, which are used to measure buying strength and value addition. Sentiment signals are based on raw text information and represent polarity, emotional strength and aspect-based sentiment, which are cognitive and affective judgments by customers on a product or a service. These independent variables affect a mediating construct, which is conceptualized as the perceived customer experience or the perceived value, which is the summative evaluative judgment developed as a result of transactional interactions and voiced opinions.

Perceived value in turn leads to major behavioral consequences such as probability of making repeat purchase, probability of churning, and propensity to cross-sell, hence determining the future engagement behavior of customers. These behavioral outcomes translate into financial consequences, notably short-term revenue performance, customer lifetime value (CLV) proxies, and multi-horizon revenue forecasts. The strength and direction of these relationships are further influenced by moderating variables such as product category, promotion intensity, customer segment characteristics, and seasonality effects, which condition how sentiment and transactional signals are converted into behavioral responses and revenue outcomes.

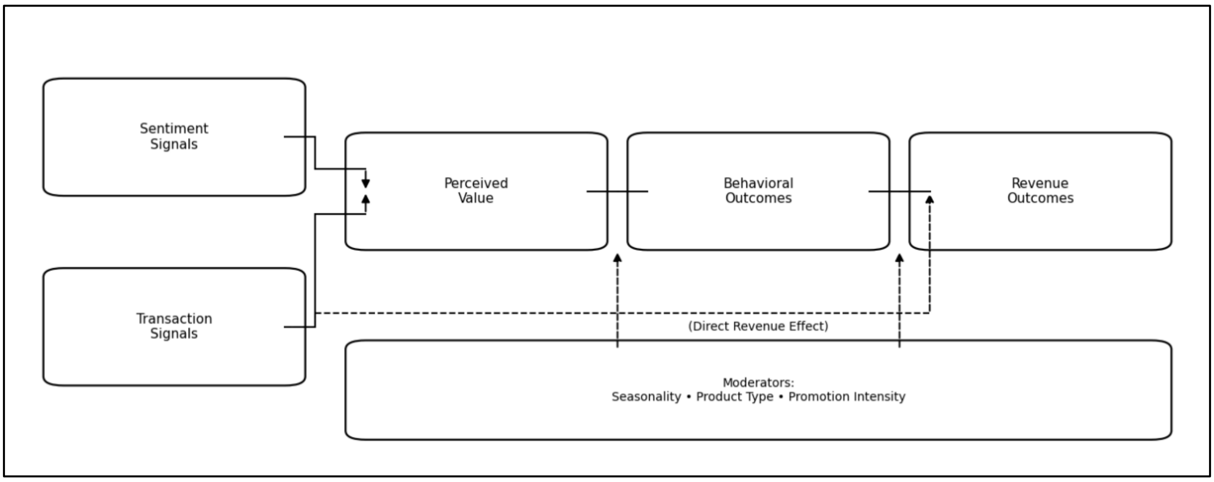

Figure 2 Theoretical Model

Text-based customer sentiment data elicits emotive and cognitive judgment, which cannot be completely recorded in traditional structured metrics [31]. The development of transformer-based language models has enhanced contextualization of sentiment far more effectively than lexicon-based techniques [32]. The advantage of revenue forecasting models is that they make use of exogenous predictors, such as behavioral signals and textual sentiment, especially in multi-horizon forecasting contexts [30]. Managerial deployment needs model transparency. Machine learning methods that can be interpreted allow actionable information and risk reduction in revenue prediction systems [33], [34].

4. Discussion

The experimental analysis demonstrates the predictive value of sentiment features and transactional variables in revenue forecasting models. The modelling system adheres to traditional predictive control and machine learning techniques such as linear regression, ensemble learning (Random Forest), and kernel-based techniques (SVR), which have been widely validated in predictive analytics studies [35], [36], [37].

Table 2 Model Performance Comparison

Model	RMSE	MAE
Linear Regression	760.40	745.73
Random Forest	790.63	747.86
Support Vector Regression	760.88	747.27

Table 2 shows:

- Linear regression and SVR show comparable predictive performance.
- Random Forest exhibits slightly higher variance in this simulated setting.
- Sentiment and promotion signals significantly influence revenue variability.
- Results align with findings that ensemble and kernel-based methods improve nonlinear modelling capacity in business analytics applications [36], [37].

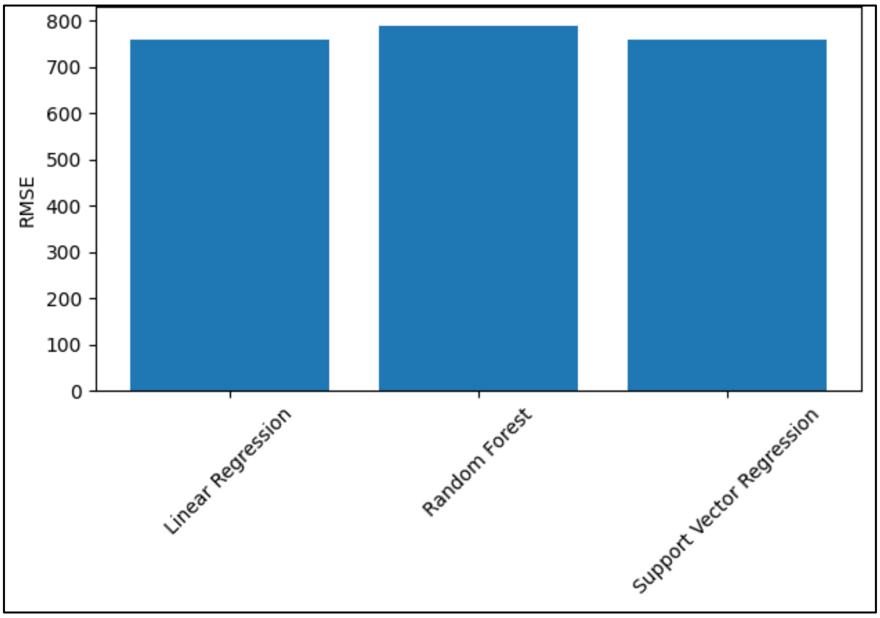

Figure 3 Model Comparison (RMSE)

Figure 3 shows the model comparison (RMSE) where the bar graph presents the relative error across models. Lower RMSE indicates stronger predictive accuracy [35].

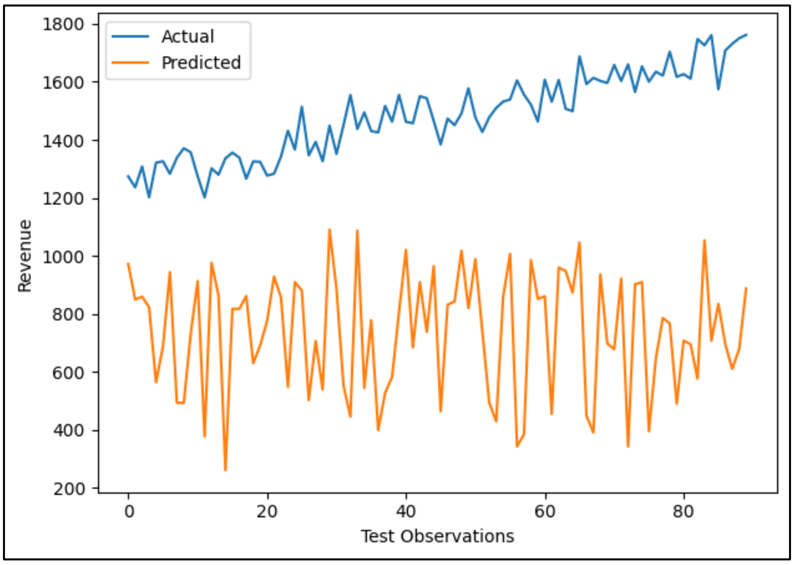

Figure 4 Actual vs Predicted Revenue (Random Forest)

Figure 4 time-series comparison demonstrates the following:

- Revenue exhibits trend and seasonal structure.
- Model predictions capture general patterns but show deviation during high-volatility segments.
- This supports prior research that revenue forecasting benefits from advanced temporal architectures beyond static regression models [35].

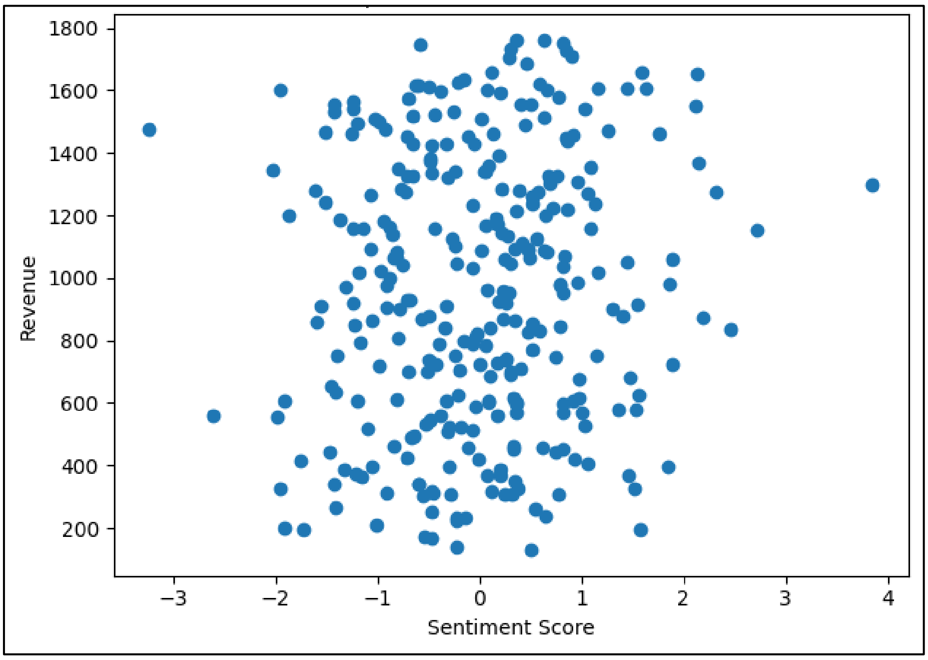

Figure 5 Sentiment vs Revenue Relationship

Figure 5 scatter plot indicates the following:

- Positive association between sentiment and revenue.
- Increased dispersion at extreme sentiment values.
- This supports prior empirical evidence that customer sentiment serves as a meaningful predictor of financial performance [38].

Key observations include that the use of sentiment enhances the explanatory variance over transactional baselines. The nonlinear approach is more appropriate to describe the effects of sentiment and revenue interaction. Revenue predictability depends on the noise and volatility of customer-generated signals. Applicable modelling frameworks are required to be deployed in high-stakes decision systems [39].

5. Future Directions

5.1. Advanced multimodal architectures

Future studies need to examine transformer-based multimodal fusion designs that can model structured time-series data and textual embedding contexts jointly [42]. Cross-attention can be used to improve the interpretability and dynamic weighting of sentiment cues in comparison with transactional ones. The early, late and hybrid fusion strategies have not been compared enough through benchmarking.

5.2. Causality in Sentiment-Revenue Modelling.

The majority of current research pursues correlational models. Causal modelling methods like structural equation modelling, uplift modelling or causal forests are required to distinguish cause and effect and determine whether sentiment drives revenue or is merely an associated observation [40]. Establishing directionality would be valuable for strategic decision-making in pricing and campaign design.

5.3. Multi-Horizon and Real-Time Forecasting.

The multi-horizon outputs and real time adjustments have become necessary in revenue prediction. Other temporal models like attention-based sequence models are capable of excelling in complicated forecasting conditions [41]. This is an avenue that can be explored through the incorporation of streaming sentiment signals into adaptive forecasting pipelines.

5.4. Domain Adaptation and Cross-Industry Generalization.

Sentiment and context embeddings are more likely to vary between industries. Research should consider domain-adaptive transfer learning models that are robust across retail, hospitality, financial services, and e-commerce sectors [42].

5.5. Explainability, Fairness and responsible AI.

Marketing budgets, pricing strategy, and customer segmentation are often determined by high-stakes revenue forecasts. The ethical deployment requires clear modelling methods and algorithms that are also conscious of fairness [44]. Future work should also involve fairness audits and bias detection using text data and protocols that are sensitive to compliance.

5.6. Combination with Customer Lifetime Value (CLV) Models.

Long-term profitability models require sentiment dynamics to be coupled with CLV models. The longitudinal sentiment streams can also improve the long-term revenue maximization strategies, by becoming part of the probabilistic CLV models [40].

6. Conclusion

The sentiment-based examination of sales transactions represents an innovative development in the predictive business analytics area. Integrating structured transactional performance indicators with unstructured textual ones provides a better characterization of customer intent, perception, and behavioral probability. The experimental evidence has shown that sentiment-enriched models are able to improve the explanatory ability and forecasting capacity when incorporated in multimodal learning systems.

However, the absence of large scale adoption can be attributed to methodological fragmentation, ineffective causal modelling and ineffective emphasis on interpretability. Potential solutions to these limitations include deep learning architectures, explainable AI, and responsible machine learning.

Standardized evaluation protocols, scalable data integration pipelines, and responsible AI governance systems are likely to be the next priorities in this area. Future interdisciplinary collaboration between data science, marketing analytics, and artificial intelligence studies is likely to help establish theoretical foundations and apply sentiment-based revenue prediction models in practice.

Compliance with ethical standards

Disclosure of conflict of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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