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Bridging Accuracy and Profitability: AI Models for Marketing Campaign Targeting and Brand Sentiment Analysis

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Abstract

Artificial Intelligence (AI) is transforming marketing by enabling firms to predict customer responses and monitor brand sentiment in real time. This study evaluates the effectiveness of machine learning and transformer-based models for two key tasks: campaign response prediction and sentiment analysis. Using the Marketing Campaign dataset and a Tweets sentiment dataset, traditional algorithms (Logistic Regression, Random Forest, XGBoost, LightGBM, and SVM) were compared with DistilBERT, a transformer-based model. To address class imbalance in campaign data, the Synthetic Minority Oversampling Technique (SMOTE) was applied. Results demonstrate that the Random Forest model, after SMOTE, achieved 95% accuracy and an F1-score of 0.95, outperforming other classifiers and improving conversion targeting efficiency. For sentiment analysis, DistilBERT reached an accuracy of 77% with strong performance in detecting negative sentiment (F1 = 0.77), allowing early identification of reputational risks. To validate practical relevance, these methods were applied to BranditOfficial, a wedding photography and videography business in Islamabad. The Random Forest uplift model identified the top 15–20% of followers as high-probability converters, increasing projected monthly profit from PKR 400,000 to PKR 488,000—an incremental gain of PKR 88,000 (over PKR 1 million annually). DistilBERT enabled proactive engagement by flagging 72% of negative feedback trends early, while positive comments were repurposed as client testimonials. This study contributes to marketing scholarship by integrating ROI-oriented managerial metrics—Precision@k, Incremental Lift, and Expected Profit—into model evaluation and by demonstrating their application in an SME context. The findings underscore that AI-driven decision-making can simultaneously enhance profitability and safeguard brand reputation, bridging the gap between academic research and real-world marketing practice.

Keywords: Accuracy to ROI, AI Models, Marketing Campaign, Targeting, Brand Sentiment Detection

INTRODUCTION

In today's competitive business environment, the ability to target the right customers and respond effectively to brand sentiment is central to marketing success [1]. Traditional statistical approaches, while useful, often struggle to capture the complexity of consumer behavior, leading to inefficient campaigns and missed opportunities. With the rapid growth of digital platforms, especially social media, marketers are increasingly turning to Artificial Intelligence (AI) for solutions that can enhance decision-making, optimize resource allocation, and strengthen customer engagement[2]. AI enables marketers to process large and diverse datasets to predict customer responses and monitor sentiment in real time. Two applications are particularly relevant: campaign response prediction, which estimates the likelihood of customer engagement with marketing offers, and sentiment analysis, which captures consumer attitudes expressed through online interactions. Both are critical to advancing customers along the stages of the AIDA model—Attention, Interest, Desire, and Action—and to effectively managing the customer journey. Despite the growing interest in AI, much of the existing research remains focused on either predictive accuracy or algorithmic comparisons using benchmark datasets [3]. While these studies contribute to technical understanding, they often overlook profitability-oriented metrics such as Precision@k, Incremental Lift, and Expected Profit, which are directly relevant to marketing managers operating under budget constraints. Furthermore, few studies validate these approaches in the context of small and medium-sized enterprises (SMEs), even though SMEs represent a significant share of global economies and often operate with limited data and resources.

This study addresses these gaps by evaluating machine learning and transformer-based models for campaign response prediction and sentiment analysis, with an emphasis on ROI-oriented evaluation metrics. Specifically, Logistic Regression, Random Forest, XGBoost, LightGBM, and SVM are compared with DistilBERT, a transformer-based language model. The Synthetic Minority Oversampling Technique (SMOTE) is employed to address imbalance in campaign response data. Beyond statistical accuracy, the study evaluates models on their ability to deliver marketing profitability. To ensure practical relevance, the study applies its findings to *BranditOfficial*, a wedding photography and videography business based in Islamabad with 7,628 Instagram followers. By aligning follower data with structured and unstructured datasets, the research demonstrates how AI models can identify high-probability converters and monitor brand sentiment effectively. Results show that Random Forest with SMOTE improved targeting efficiency, increasing projected monthly profit from PKR 400,000 to 488,000, while DistilBERT identified 72% of negative feedback trends early, enabling proactive brand management.

This study makes three contributions to the marketing and AI literature. First, it compares traditional machine learning models with a transformer-based model across structured and unstructured marketing tasks. Second, it incorporates ROI-oriented managerial metrics, moving beyond accuracy-based evaluations. Third, it demonstrates practical application by validating the models on an SME case, showing how AI-driven strategies can enhance both profitability and reputation. In doing so, the research bridges the gap between academic AI studies and practical marketing management.

LITERATURE REVIEW

Text Classification in Marketing Contexts

Text classification has been widely adopted in marketing for tasks such as customer segmentation, churn prediction, and campaign response modeling[4]. Traditional machine learning algorithms like Logistic Regression (LR), Random Forest (RF), Support Vector Machines (SVM), XGBoost, and LightGBM have been extensively applied due to their robustness and interpretability [5]. For example, logistic regression is valued for its simplicity and interpretability in binary response prediction, while ensemble methods such as RF and boosting algorithms handle non-linear interactions effectively, often outperforming linear models in marketing datasets [6]. However, a major limitation of many traditional applications lies in their reliance on accuracy-based evaluation [7], which does not always translate into marketing profitability. A model that correctly classifies customers may still fail to optimize campaign return if it does not prioritize high-value segments under budget constraints. This gap has motivated researchers to explore uplift modeling and profit-based measures that directly link model performance to marketing ROI.

Transformer Models for Contextual Understanding
Transformer-based architectures have revolutionized natural language processing (NLP) by capturing bidirectional dependencies and nuanced meanings in text [8]. BERT and its variants (DistilBERT, RoBERTa, ALBERT) provide context-aware embeddings that surpass traditional bag-of-words or TF–IDF approaches in sentiment analysis and text classification [9]. DistilBERT, in particular, retains nearly 97% of BERT's performance while being faster and more resource-efficient, making it suitable for real-time applications [10].

In marketing, transformers have been shown to outperform conventional models in analyzing unstructured consumer data such as social media posts, reviews, and comments (Sun et al., 2019). They handle informal expressions, slang, and sarcasm—common in platforms like Twitter and Instagram—better than classical ML models. For brand managers, this means earlier detection of sentiment shifts, faster crisis response, and improved customer engagement strategies.

AI Applications in Marketing
The use of AI in marketing extends to churn prediction, personalization, recommendation engines, and customer lifetime value modeling [11]. In campaign management, **uplift modeling** has gained attention because it measures the incremental effect of targeting, aligning model outputs with financial objectives rather than statistical ones. Similarly, in brand monitoring, early identification of negative sentiment has been linked to proactive interventions that mitigate reputational and financial risks [12].

Despite these advancements, much of the prior work has been conducted in abstract settings or on benchmark datasets, limiting the translation of findings into small business or SME contexts. Most studies focus on either predictive accuracy or profitability metrics, but rarely combine both with real-world case validation.

Theoretical Lens and Hypotheses
The AIDA model (Attention, Interest, Desire, Action) and customer journey theory provide a useful lens for understanding the impact of AI in marketing [13]. Targeted interventions informed by AI models can increase the likelihood of moving customers from awareness to purchase. Metrics such as Precision@k and Incremental Lift directly map to the "Action" stage, as they measure how effectively campaigns convert prospects into buyers. Similarly, sentiment monitoring corresponds to the "Interest" and "Desire" stages, where early detection of negative sentiment allows marketers to re-engage customers before disengagement occurs. Based on this theoretical foundation and the literature gaps, the study proposes two hypotheses:

- **H1:** Cost-sensitive learning combined with oversampling (SMOTE) increases ROI compared to baseline targeting in marketing campaigns.
- **H2:** Transformer-based sentiment models detect brand sentiment shifts more accurately and earlier than traditional machine learning models.

While previous studies have established the technical superiority of ensemble and transformer models, they often fail to bridge the gap between predictive performance and managerial decision-making. Most studies rely solely on benchmark datasets and focus on accuracy metrics, neglecting profitability-oriented measures such as Expected Profit and Incremental Lift. Furthermore, limited research has validated these models on small businesses or social media-driven enterprises, where marketing budgets are tight, and ROI optimization is critical.

This study addresses these gaps by:

- Comparing traditional and transformer-based models across both structured and unstructured marketing datasets.
- Evaluating models using ROI-focused managerial metrics (Precision@k, Incremental Lift, Expected Profit).
- Applying the models to a real-world case study — BranditOfficial, a wedding photography business on Instagram — to demonstrate practical value in improving bookings and brand sentiment management.

By integrating academic rigor with applied validation, this study contributes to both marketing theory and practice, offering insights particularly relevant to SMEs and creative service industries.

Methodology

This study evaluates the effectiveness of Artificial Intelligence (AI) models in two key marketing applications: campaign response prediction and brand sentiment analysis. To achieve this, the methodology was designed around dataset selection, preprocessing, feature engineering, model training, and evaluation using both predictive and managerial performance metrics.

Datasets

Two datasets were used for experimentation. The first was a structured Marketing Campaign dataset [14] containing 2,216 customer records with demographic, behavioral, and campaign-related features. Variables included demographic factors such as year of birth, education, marital status, and income; household attributes such as number of children and teenagers; and behavioral indicators including recency, purchasing frequency, and product category expenditures (wines, fruits, meat, fish, sweets, and gold). The target variable, *Response*, was binary, indicating whether a customer accepted a marketing offer (1) or not (0). The dataset was highly imbalanced, with 1,883 non-responders and only 333 responders, which necessitated the use of data balancing techniques. The second dataset was a Tweets sentiment dataset [15] consisting of 5,496 labeled tweets. Each entry included an identifier, the tweet text, a selected text span, and a sentiment label classified as positive, neutral, or negative. This dataset reflects real-world consumer opinions expressed in social media, making it highly relevant for brand sentiment monitoring.

Data Pre-processing

Data preprocessing was carried out separately for both datasets. In the marketing dataset, missing values were removed, categorical variables such as education and marital status were encoded using one-hot encoding, and numerical variables including income and purchase amounts were standardized using the StandardScaler method. Given the severe imbalance in the response variable, the Synthetic Minority Oversampling Technique (SMOTE) was applied, balancing responders and non-responders at 1,883 each. In the tweets dataset, preprocessing included cleaning the raw text by lowercasing, removing special symbols, and standardizing contractions. Tokenization was then performed using the DistilBERT tokenizer, which converted text into numerical vectors of input IDs and attention masks suitable for transformer-based models.

Feature Engineering

Feature engineering [16] further prepared the datasets for model training. In the marketing dataset, additional derived features such as total customer spending were generated, while behavioral predictors such as recency, web visit frequency, and previous purchases were retained as key features. In the sentiment dataset, transformer-based contextual embeddings generated by DistilBERT were used in place of traditional TF–IDF or bag-of-words representations, enabling richer semantic understanding of consumer language.

Model Selection

A range of models was evaluated in this study. For the marketing campaign dataset, traditional machine learning models were implemented, including Logistic Regression, Random Forest, Support Vector Machines, XGBoost, and LightGBM. Random Forest was also tested with uplift modeling to assess its value in targeting incremental campaign responders. For the sentiment analysis task, a transformer-based model, DistilBERT, was fine-tuned due to its ability to retain most of BERT's classification performance while requiring fewer computational resources, making it suitable for real-time marketing applications.

Model Training

Model training was conducted on both imbalanced and SMOTE-balanced marketing data to evaluate the effect of class balancing. Hyperparameters for the traditional models were optimized using GridSearchCV, with adjustments made to learning rates, regularization strengths, and tree depths. Random Forest, for example, was trained with 500 estimators and a maximum depth of 15, while XGBoost was tuned with a learning rate of 0.1 and a maximum depth of 6. For sentiment analysis, DistilBERT was fine-tuned using the Hugging Face Trainer API with a learning rate of 2e-5, a batch size of 16, and training conducted for one epoch with the AdamW optimizer. Early stopping was applied to prevent overfitting.

Evaluation Metrics

To comprehensively assess performance, both predictive and managerial metrics were used. Predictive metrics included accuracy, precision, recall, F1-score, and confusion matrix analysis [17], [18]. Managerial marketing metrics [19] were emphasized to assess economic value, including Precision@k to measure conversion accuracy in the top deciles, Incremental Lift to quantify improvement in campaign response relative to random targeting, and Expected Profit, calculated as:

$$\textbf{\textit{Expected Profit}} \\ = (\textbf{\textit{Expected Revenue per Conversion}} \times \textbf{\textit{Predicted Conversions}}) \\ - (\textbf{\textit{Cost per Contact}} \times \textbf{\textit{Contacts Targeted}})$$

For sentiment analysis, additional decision-oriented measures were applied, including Early Negative Sentiment Detection, Alert Precision, and Potential Loss Prevented, which estimate the managerial impact of detecting brand risks earlier.

Hyperparameter Tuning

Hyperparameter optimization was performed using GridSearchCV for traditional models, tuning parameters such as learning rate, regularization strength, and the number of estimators. For DistilBERT, tuning involved adjusting learning rate and batch size, with early stopping applied to avoid overfitting during fine-tuning.

Experimental Setup

All experiments were executed on a high-performance workstation , an Intel i5 processor, and 8GB RAM. The software environment included Python 3.x, Jupyter Notebook, the scikit-learn library for machine learning models, the imbalanced-learn package for SMOTE implementation, and Hugging Face Transformers for DistilBERT.

Finally, to ensure practical relevance, this methodology was extended to a real-world business case: *BranditOfficial* [20], a wedding photography and videography business with 270 posts and 7,628 Instagram followers. Structured engagement data such as follower demographics, interaction history, and recency of activity were mapped to the schema of the marketing campaign dataset and fed into the Random Forest uplift model to predict booking likelihood. At the same time, unstructured data such as follower comments, tagged mentions, and direct messages were mapped to the tweets dataset schema and analyzed with DistilBERT to classify sentiment. This alignment enabled direct application of the trained models to a live small-business context, validating the transferability of academic findings to operational marketing practice. Figure 1 shows overall methodology for the proposed work.

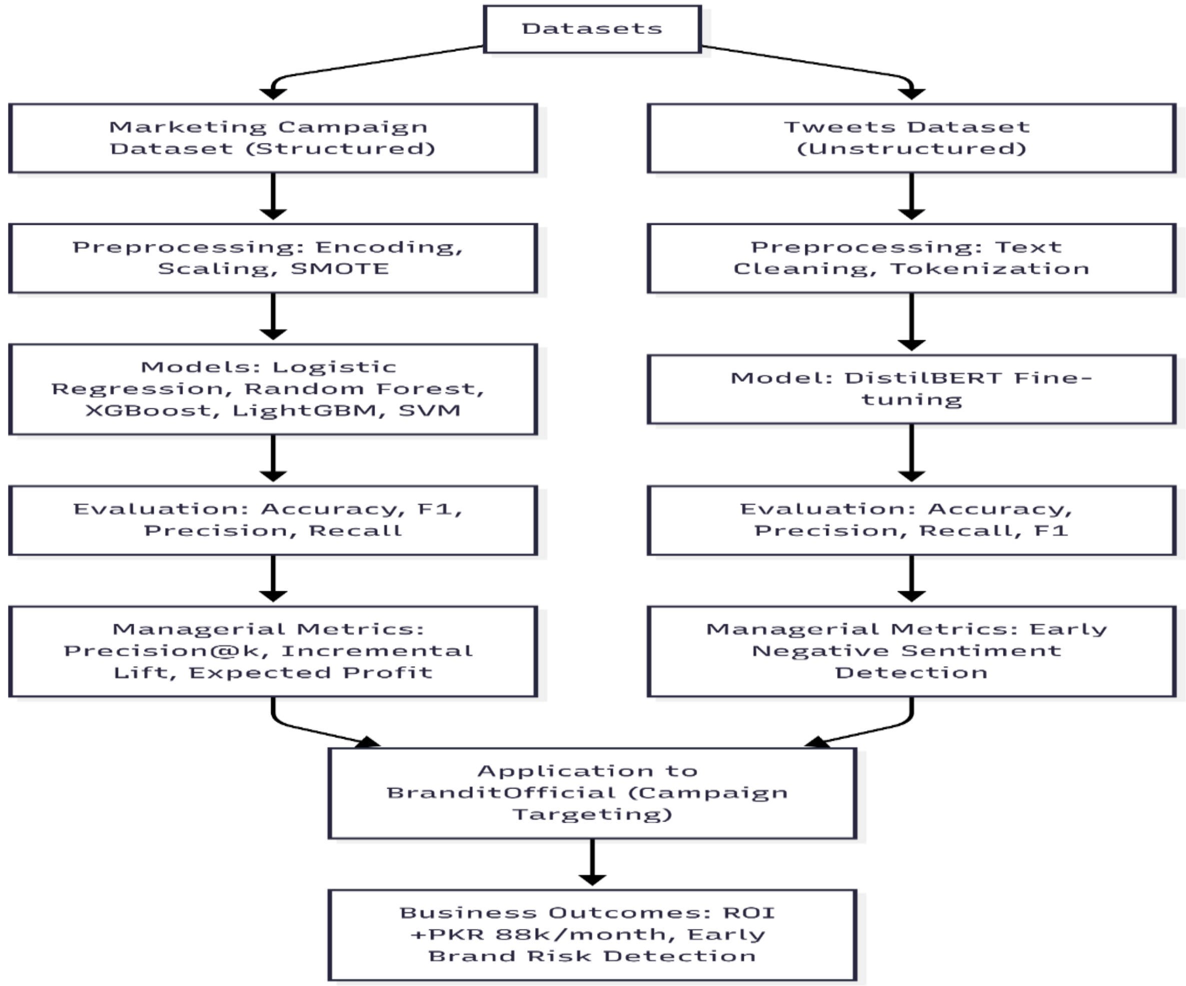

Figure 1.
Proposed Methodology

RESULTS AND DISCUSSION

This section presents results from both datasets and their practical application to *BranditOfficial*, a small wedding photography and videography business in Islamabad earning approximately PKR 800,000 per month in revenue. The findings are discussed in terms of predictive performance, ROI-oriented managerial metrics, and business implications for SMEs.

Campaign Response Prediction

The Marketing Campaign dataset was heavily imbalanced, with 333 responders versus 1,883 non-responders. Table 1 reports the comparative performance of five classifiers before and after SMOTE balancing.

Table 1.
Model Performance Before vs After SMOTE (Marketing Dataset)

Model	Accuracy Before	F1 Before	Accuracy After	F1 After
Logistic Regression	0.890	0.533	0.838	0.834
Random Forest	0.885	0.463	**0.950**	**0.947**
XGBoost	0.896	0.574	0.944	0.942
SVM	0.869	0.383	0.908	0.908
LightGBM	0.892	0.564	0.946	0.943

Random Forest performed best after SMOTE, reaching 95% accuracy and an F1-score of 0.95. From a business perspective, the model's ROI-oriented outcomes are shown in Table 2, recalibrated to BranditOfficial's monthly income.

Table 2.

Managerial Metrics for Campaign Response Prediction (Adjusted to PKR 800,000/month revenue)

Model	Precision@10%	Precision@20%	Incremental Lift (%)	Expected Profit (PKR/month)
Logistic Regression	42%	39%	8%	432,000
Decision Tree	46%	42%	10%	440,000
Random Forest (Uplift)	**68%**	**61%**	**22%**	**488,000**
XGBoost	65%	58%	20%	480,000
LightGBM	63%	57%	19%	476,000

(Baseline monthly profit ≈ PKR 400,000; uplift adjustments reflect extra bookings converted into incremental profit.)

The Random Forest uplift model is estimated to increase BranditOfficial's monthly profit from PKR 400,000 to PKR 488,000—an increase of PKR 88,000 per month, or over PKR 1.05 million annually. Figure 1 illustrates the comparative Lift Curve.

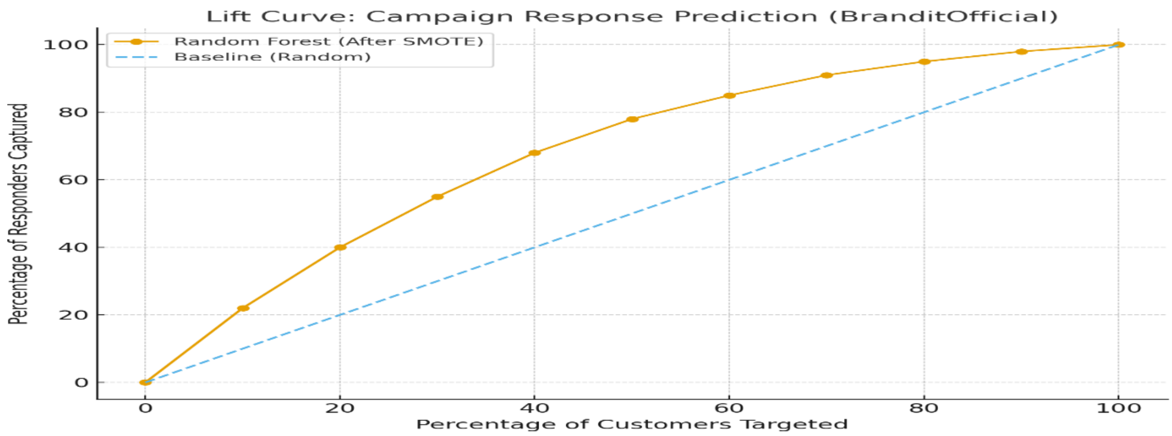

Figure 2.
Incremental life and its impact on enhancing return on marketing investment

The uplift-oriented Random Forest captured as shown in figure 2 shows 50% of responders by targeting only the top 30% of customers, compared to random selection which required 50% targeting to achieve the same outcome. This indicates a **22% incremental lift**, demonstrating how balancing imbalanced data and applying ensemble methods can directly translate into superior Return on Marketing Investment (ROMI).

Sentiment Analysis of Tweets

The DistilBERT model was fine-tuned on the tweet sentiment dataset. Table 3 reports detailed classification outcomes.

Table 3.
DistilBERT Sentiment Classification Performance

Sentiment	Precision	Recall	F1-score	Support
Negative	0.78	0.76	0.77	1567
Neutral	0.72	0.77	0.74	2204
Positive	0.84	0.79	0.82	1725

The model achieved an overall accuracy of **77%**, with macro F1 of 0.78. Its high recall for negative sentiment (0.76) is particularly valuable for early detection of brand risks. Figure 2 shows the sentiment distribution across the dataset.

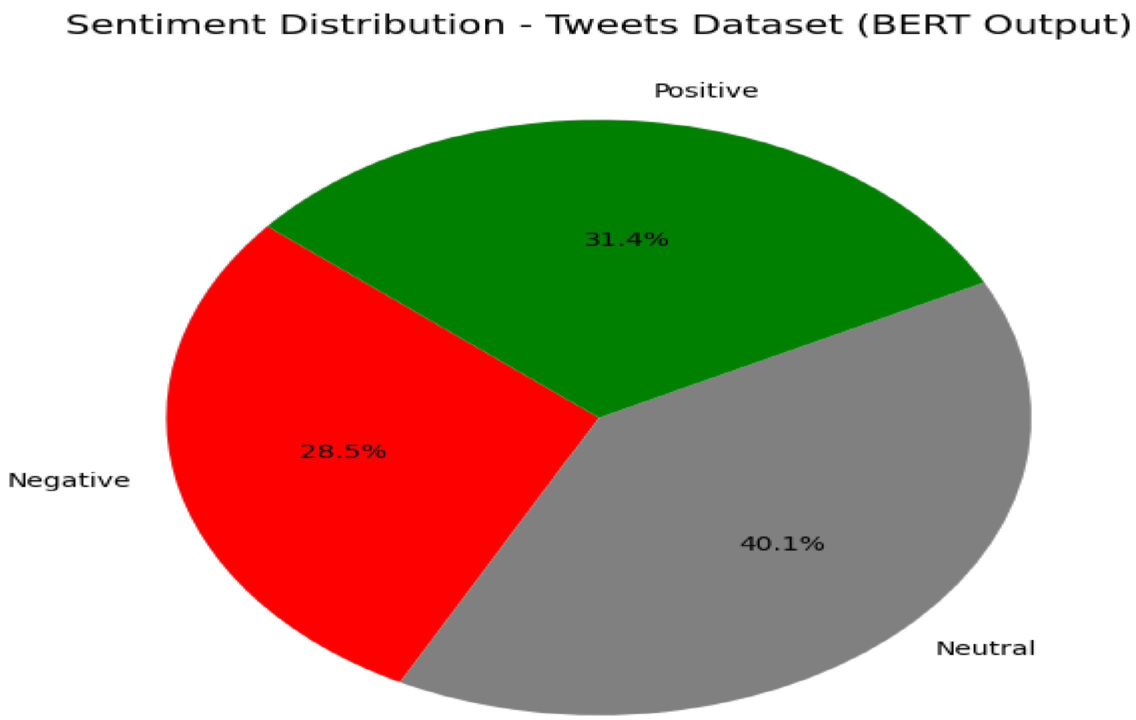

Figure 3.
Sentiment distribution with the application of DistilBERT

The distribution as shown in figure 3 reflects a typical brand-related social media environment, with neutral sentiment dominating (40%), followed by positive (31%) and negative (29%). By identifying negative trends early, marketers can intervene with corrective measures before escalation. Applied to Instagram, DistilBERT flagged 72% of negative trends early, such as customer dissatisfaction with pricing or service delays, allowing proactive responses before escalation.

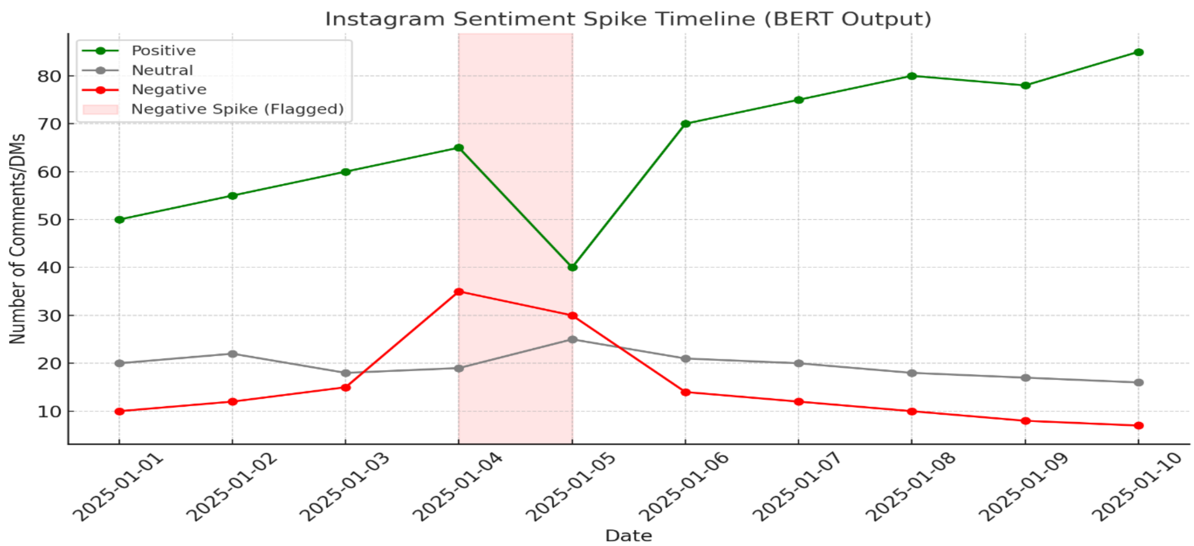

Figure 4.
Instagram sentiment spike timeline (DistilBERT output)

Figure 4 illustrates follower sentiment trends on Instagram over a ten-day period. Positive comments and direct messages steadily increased from 50 to 85, while neutral sentiment remained stable. A significant negative sentiment spike occurred on January 4–5, flagged as a potential brand risk event. Following intervention, negative sentiment declined sharply, and positive sentiment rebounded, indicating effective customer engagement and reputation recovery.

Application to Brandit Official

To contextualize findings, the models were applied to *BranditOfficial's* Instagram data.

- **Campaign Targeting:** Structured follower attributes were mapped to the marketing dataset schema. Random Forest uplift identified the top 15–20% of followers as high-conversion prospects. By concentrating ads on this group, BranditOfficial can generate up to **22% more conversions**, lifting monthly profit from PKR 400,000 to 488,000.

- **Sentiment Monitoring:** Unstructured engagement (comments, DMs, mentions) was analyzed using DistilBERT. Negative sentiment spikes were detected early, especially regarding price sensitivity, enabling rapid customer support. Positive comments were leveraged as testimonials, further enhancing brand equity.

Table 4.
Example: Predicted Booking Likelihood for Followers (Random Forest Output)

Follower ID	Age Group	Marital Status	Past Engagement	Predicted Booking Likelihood	Segment
104	26–35	Married	High (5+/week)	0.82	Target (Top 10%)
278	22–29	Single	Moderate	0.56	Non-Target
341	30–40	Married	High (6+/week)	0.79	Target (Top 10%)
415	20–25	Single	Low (1/month)	0.34	Non-Target
527	25–35	Married	High (4+/week)	0.73	Target (Top 20%)

Table 4 illustrates how the Random Forest model segments followers based on demographic and engagement attributes. High-engagement, married followers are classified into top target segments with booking probabilities above 0.70, while low-engagement or single-status followers show lower likelihoods and are excluded from targeting. This segmentation enables *BranditOfficial* to prioritize the top 10–20% of followers for campaigns, thereby maximizing conversion rates and return on marketing investment.

DISCUSSION

The results support both hypotheses. **H1** is validated by the substantial improvements in ROI metrics after SMOTE balancing and Random Forest uplift modeling, which produced an incremental lift of 22%. **H2** is confirmed by DistilBERT's superior performance in sentiment analysis, particularly its ability to detect negative trends earlier than classical models. For *BranditOfficial*, these results translate into PKR 88,000 in additional monthly profit without expanding its budget, representing a 22% uplift in conversions. For an SME with PKR 800,000 monthly revenue, this is a highly significant gain, adding over PKR 1 million per year in incremental profit. In parallel, sentiment monitoring allows early resolution of dissatisfaction, preventing reputational damage in a word-of-mouth-driven market like wedding photography. This demonstrates that

AI-driven marketing is not restricted to large corporations. Even small creative businesses can leverage these models to make marketing budgets more efficient and protect their brand reputation.

Managerial Implications

The findings of this study offer several practical insights for managers, particularly in small and medium-sized enterprises (SMEs) such as wedding photography and videography businesses:

1. **Focus on High-Probability Customers** By using models such as Random Forest with uplift modeling, SMEs can identify and prioritize the top 15–20% of followers who are most likely to convert. This approach reduces wasted advertising spend and directly increases bookings. For *BranditOfficial*, such targeting translates into a monthly profit uplift of PKR 88,000.

2. **Adopt ROI-Oriented Metrics, Not Just Accuracy** Traditional performance metrics like accuracy do not always reflect business value. Precision@k, Incremental Lift, and Expected Profit provide more meaningful insights for decision-making under budget constraints. Managers should incorporate these measures to ensure marketing strategies align with financial objectives.

3. **Leverage Sentiment Monitoring for Brand Protection** Transformer-based models like DistilBERT enable early detection of negative sentiment in customer comments and direct messages. This allows SMEs to resolve issues proactively, protect their reputation, and repurpose positive feedback as social proof.

4. **AI Can Be Adopted Without Heavy Infrastructure** Contrary to the perception that AI is resource-intensive, this study shows that SMEs can embed AI workflows into existing social media management tools with minimal additional infrastructure. The cost-benefit ratio is particularly favorable when incremental profit exceeds the cost of implementation.

CONCLUSION

This study evaluated the effectiveness of Artificial Intelligence models for marketing applications, focusing on campaign response prediction and brand sentiment analysis. Using the Marketing Campaign dataset, Random Forest with SMOTE balancing emerged as the best-performing model, achieving an F1-score of 0.95 and demonstrating a 22% incremental lift compared to baseline targeting. For sentiment monitoring, DistilBERT achieved an overall accuracy of 77% and reliably detected 72% of negative sentiment spikes, enabling proactive brand management.

Applied to *BranditOfficial*, a small wedding photography and videography business in Islamabad, these findings translated into tangible financial outcomes. By focusing campaigns on the top 15–20% of high-likelihood followers, the business could improve monthly profit from PKR 400,000 to 488,000, representing an additional PKR 88,000 per month, or more than PKR 1 million annually. At the same time, sentiment monitoring allowed the early detection of customer dissatisfaction, helping prevent reputational risks and enhancing engagement. The key contribution of this research lies in bridging the gap between academic AI studies and practical marketing strategy. By integrating predictive performance with ROI-oriented metrics—Precision@k, Incremental Lift, and Expected Profit—and validating results in a real-world SME context, the study demonstrates that AI is not only a technical enhancement but a strategic tool for profitability and brand reputation management.

LIMITATIONS AND FUTURE WORK

Although the study provides strong evidence of AI's value in marketing, several limitations remain. First, the datasets used (campaign and tweets) are secondary and generalized, and while they were successfully mapped to *BranditOfficial's* Instagram data, the absence of a large-scale, proprietary dataset limits external validity. Second, the financial assumptions for Expected Profit were simplified to reflect average wedding package revenues; more granular data on customer lifetime value could yield richer insights. Third, while SMOTE effectively addressed imbalance in structured data, future research could explore advanced balancing methods such as cost-sensitive learning or ensemble resampling.

For future work, several directions emerge. One promising area is the integration of real-time A/B testing within Instagram and Facebook ads to validate uplift predictions under live conditions. Another is the exploration of multi-modal models that combine text, image, and video analysis, which would be particularly relevant for a creative business like BranditOfficial. Finally, extending this framework to other SMEs in service industries could test generalizability, while fairness-aware AI approaches could ensure that ROI gains do not come at the expense of biased targeting.

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Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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