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Stacking Ensemble Revenue Predictions in Digital Marketing: A SHAP-Based Analysis of Price and Quantity as Key Predictors

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Abstract. This study focuses on developing a digital marketing conversion prediction model using an ensemble stacking approach combined with explainable artificial intelligence (XAI) methods to improve model transparency. The primary objective of this study is to investigate the impact of price and product quantity on revenue predictions, as well as to gain a clearer understanding of the factors that influence customer purchasing behaviour in the context of digital sales. The methodology used includes data collection from a Kaggle dataset containing 3,000 records and 15 features related to customer demographics, product information, and marketing channels. The preprocessing stage ensures data quality, followed by feature engineering and model development using an ensemble stacking model consisting of Logistic Regression, Gaussian Naïve Bayes, and Support Vector Classification. Model evaluation was conducted using precision, recall, F1-score, and ROC-AUC metrics, with performance improvements achieved through cross-validation and probabilistic calibration. The study results showed that model accuracy reached 0.97, with significant contributions from price and product quantity features, as seen in the SHAP analysis. The ensemble stacking model provided stable and reliable predictions. These findings underscore the importance of effective pricing strategies and product volume optimisation in driving revenue growth. The use of SHAP enhances interpretability, enabling businesses to make more informed decisions. This research contributes to the development of transparent and practical machine learning applications in digital marketing, providing valuable implications for business strategy optimization.

Keywords: digital marketing, conversion prediction, stacking ensemble model, explainable AI (XAI), SHAP (Shapley Additive Explanations)

1. INTRODUCTION

The rapid development of digital technology has presented significant opportunities and challenges in modern marketing strategies. Limitations in tools, knowledge, and expertise in implementing digital marketing often hinder revenue growth [1]. Additionally, the complexity of identifying digital revenue, fluctuations in online advertising costs, and the dynamics of digital asset valuation further exacerbate the situation [2]. The explosion of digital channels and competition in leveraging big data also complicates the process of adjusting revenue strategies [3]. Businesses face significant obstacles in building digital revenue, influenced by limitations in skills, funding, and access to technology [4]. These issues highlight a fundamental gap between the potential of digital technology and businesses' ability to optimize it for economic value creation.

In relation to these issues, various studies have also emphasized the fundamental challenges in implementing digital marketing. The importance of adjusting post-COVID-19 strategies, particularly in response to changes in consumer behavior and demands for marketing cost efficiency, has been increasingly emphasized [5]. Limited financial resources, human resources, and technological understanding often pose significant barriers for businesses in adapting to digitalization [6], [7]. Additionally, intensifying competition, changes in customer behavior, and difficulties in building brand awareness are critical challenges that must be addressed [8]. The explosion of digital channels and competition in the use of big data also forces businesses to continuously adjust their marketing strategies to achieve optimal results [3]. Therefore, the success of digital marketing depends not only on the availability of technology, but also on the organization's ability to adapt, formulate effective

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strategies, and manage resources to overcome existing complexities.

This study aims to explore and understand the factors that influence revenue predictions in digital transactions, particularly in the context of data-driven marketing. Using machine learning techniques, this study aims to develop effective predictive models that identify key patterns, enabling companies to design more efficient digital marketing strategies. Additionally, this research aims to explore the application of explainable AI techniques such as SHAP (SHapley Additive exPlanations) to provide more transparent interpretations of decisions generated by machine learning models.

The primary contribution of this research is to provide deeper insights into how specific factors in digital transactions can impact revenue. By using the stacking ensemble method, which combines multiple predictive models to improve accuracy, this research contributes to the development of more reliable predictive models in the context of digital transaction data. Additionally, the explainable AI approach plays a crucial role in creating model transparency, enabling stakeholders to more easily understand how each feature, such as price and product quantity, influences the decisions generated by the model. These findings are expected to help businesses formulate more data-driven marketing strategies, enhance operational efficiency, and optimize marketing decisions by leveraging more transparent and easily understandable technology.

2. RELATED WORK

Conversion prediction in digital marketing has become a topic of widespread interest in the literature. With advances in machine learning (ML) technology and big data analysis, many studies have proposed sophisticated methods to improve prediction accuracy in this context. Various methods have been applied to predict digital conversions, each with its own level of success and limitations. One study proposed the use of SE-stacking models to predict user purchasing behavior, showing that combining information from multiple predictive models can improve prediction accuracy [9]. However, this study did not emphasize an understanding of the factors that clearly contribute to prediction outcomes. On the other hand, another study focusing on the application of SHAP in demand forecasting emphasizes the importance of model interpretability in enhancing the practical application of machine learning [10].

Further research proposes the use of stacked ensemble models to predict Customer Lifetime Value (CLV), which is closely related to predicting user behavior in digital marketing [11]. Stacked ensemble models have been shown to outperform single models with significant improvements in prediction accuracy. However, this study focuses more on CLV prediction and does not fully consider factors influencing purchasing decisions in a broader context, such as price and quantity.

Other research indicates that the use of Temporal Fusion Transformer (TFT) can enhance the accuracy of online advertising revenue predictions by incorporating various covariates. However, this model is highly complex and may be challenging to apply in simpler business scenarios or with limited data [12].

The advantage of Stacking Ensemble in digital marketing lies in its ability to integrate various models, reducing reliance on the weaknesses of a single model. For example, research shows that using three ML algorithms simultaneously can improve marketing strategies in the food delivery business [13], [14]. This technique shows great potential for improving prediction accuracy across various sectors. However, the main drawback of this approach is the potential for overfitting and high computational costs, especially when handling large datasets, which can affect real-time performance.

Challenges in e-commerce data-based price prediction using multiple regression have shown that data transformation can significantly improve prediction accuracy [15]. However, this approach has weaknesses in handling highly varied categorical data, which is often found in the context of digital marketing.

Based on the existing literature review, several gaps in the research need to be explored further, particularly in the application of the Stacking Ensemble model for revenue and conversion prediction in digital marketing. Some of these gaps include:

- Many previous studies have emphasized the importance of feature selection in improving prediction accuracy. However, there are no clear boundaries regarding which features are most significant in the context of price and quantity [9], [11]. Therefore, this study aims to explore the contribution of price and quantity factors in greater depth and use SHAP to provide a more straightforward interpretation.
- Although many machine learning models are accurate, they are often opaque, making it challenging to understand the factors that influence prediction outcomes in practical business applications [10]. This study aims to address this issue by applying SHAP to enhance model interpretability, thereby strengthening confidence in the generated decisions.
- Many previous studies have focused on deep learning techniques, such as the Temporal Fusion Transformer (TFT), which has proven effective but requires large amounts of data and high computational resources [12]. This study proposes an alternative approach by combining lighter and more effective methods using Stacking Ensemble to produce more stable and easily interpretable predictions.

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3. METHODS

This research method was systematically designed to analyze the factors influencing digital transaction revenue using a machine learning approach, as illustrated in Figure 1. The main stages include data processing and exploration, target variable formation, predictive model development using a stacking ensemble, model performance evaluation using various metrics, and interpretation of results through an explainable artificial intelligence (XAI) approach.

Fig. 1. Proposed Method

3.1. Data Collection

Table 1 shows the features of the dataset used. This dataset, obtained from Kaggle, comprises 3,000 records and 15 features covering customer, product, and marketing activity information, making it suitable for descriptive, diagnostic, and predictive analysis related to digital sales patterns.

TABLE 1. Feature Dataset

No	Feature	Description
1	date	Transaction date
2	first_name	Customer's first name
3	last_name	Customer's last name
4	email	Customer's email address
5	gender	Customer's gender
6	ip_address	Customer's device IP address
7	product_name	Name of product purchased
8	category	Product category
9	price	Product unit price
10	quantity	Number of products purchased
11	revenue	Total transaction revenue
12	customer_country	Customer's country of origin
13	platform	The platform used by the customer
14	marketing_channel	The marketing channel that influenced the transaction
15	nps_score	Customer satisfaction and loyalty score: Net Promoter Score

3.2. Preprocessing Data

Data preprocessing includes converting date variables to the datetime type, checking for missing values, and identifying potential irregularities to ensure the quality and consistency of the dataset prior to analysis and modeling.

3.3. Exploratory Data Analysis

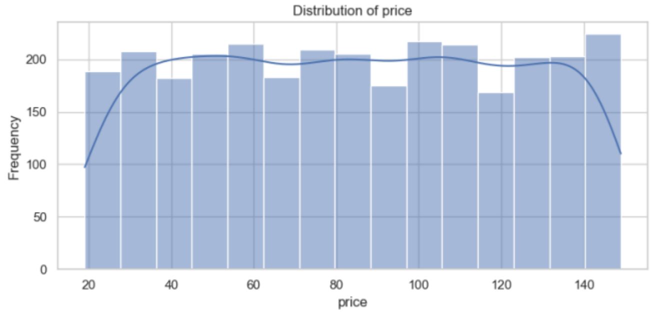

Fig. 2. Distribution of Price

Figure 2 shows the results of data exploration, indicating that the price distribution is relatively even within the range of 20 to 150, with no dominance in any particular range.

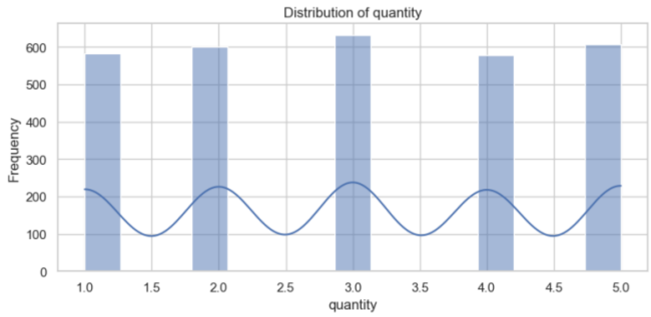

Fig. 3. Distribution of Quantity

Figure 3 shows that the quantity variable is discrete with an almost balanced distribution pattern at values of 1 to 5, indicating variation in product demand with small to moderate purchase quantities.

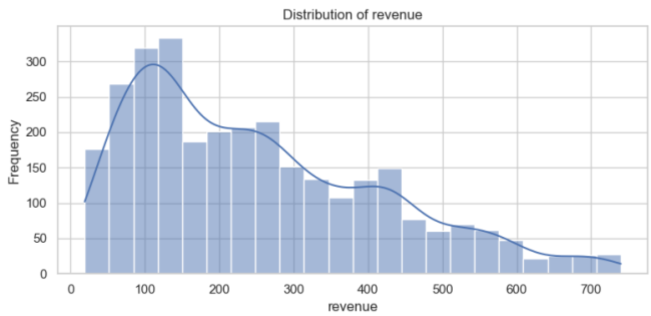

Fig. 4. Distribution of Revenue

Figure 4 is a revenue distribution graph showing a right-skewed distribution, where most transactions generate

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low to moderate revenues, while only a few transactions generate very high revenues.

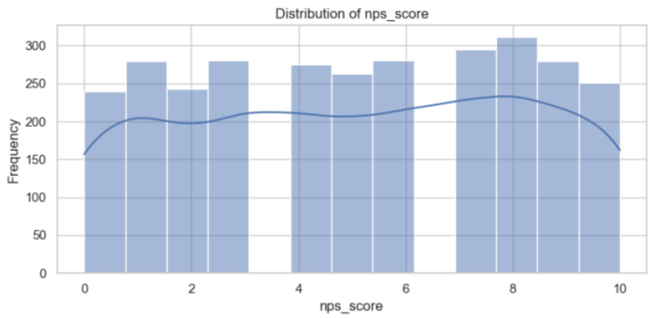

Fig. 5. Distribution of nps_score

Figure 5 is a distribution graph for the nps_score variable, where the distribution appears fairly even within the range of 0 to 10, indicating diversity in customer loyalty levels.

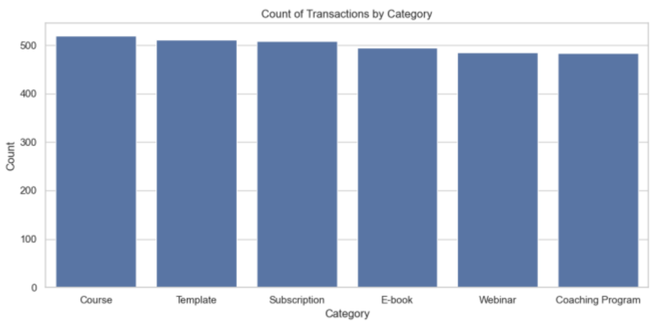

Fig. 6. Count of Transactions by Category

Figure 6 is a graph of the number of transactions for each category. Categorical analysis reveals that transactions are evenly distributed across all product categories, including Courses, Templates, Subscriptions, E-books, Webinars, and Training Programs, without any significant dominance in a particular category. These findings provide an initial overview of a relatively balanced digital sales structure, with the potential for significant influence on revenue distribution from price variations and purchase quantities.

3.4. Feature Engineering and Labeling

Feature engineering was performed by creating a binary target variable, high_revenue, using the median split approach, accompanied by the selection of relevant features such as price, quantity, nps_score, category, marketing channel, and the application of one-hot encoding on categorical variables to ensure optimal numerical representation in modeling.

3.5. Data Split

The data is split using the train-test split method with a ratio of 70% for training and 30% for testing, along with `random_state=42` to ensure consistency and reproducibility of results.

3.6. Modelling

Modeling was performed using stacking ensembles that combine several base models, namely Logistic Regression, GaussianNB, SGDClassifier, and Support Vector Classifier, with an SGDClassifier meta learner based on log loss, as shown in Figure 7. The training process utilizes five-fold cross-validation to enhance performance reliability and facilitate parallel processing for efficiency, then tests the model on the test data to generate class predictions and probabilities.

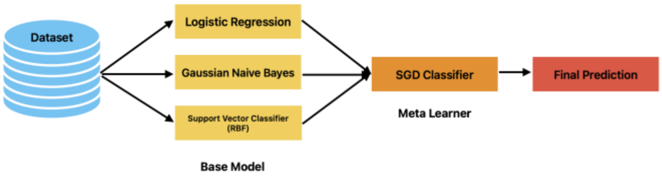

Fig. 7. Stacking Ensemble Architecture

3.7. Evaluation Model

Model evaluation encompasses accuracy analysis, confusion matrix, ROC-AUC, learning curve, probability calibration, and error distribution, providing a comprehensive assessment of performance, stability, and potential overfitting.

3.8. Explainable AI

The SHAP method is used to explain model predictions, with summary diagrams identifying the global contributions of features and waterfall diagrams illustrating the influence of features on individual predictions, thereby making model decisions more transparent.

4. RESULTS AND DISCUSSIONS

4.1. Results

The training process employs a stacked ensemble approach, which combines several heterogeneous base models, including Logistic Regression, Gaussian Naïve Bayes, SGDClassifier, and RBF kernel-based Support Vector Classification. These base models were chosen because they are capable of capturing data characteristics from both linear and non-linear perspectives. Next, the meta-model, namely SGD with a logistic loss function, is trained using the probabilistic predictions of the base models on out-of-fold data through five-fold cross-validation. This strategy is effective in reducing bias and variance while minimizing the risk of overfitting, as shown in Table 2.

TABLE 2. Evaluation Model of Stacking Ensemble

Class / Metric	Precision	Recall	F1-Score	Support
0	0.96	0.99	0.97	452
1	0.99	0.96	0.97	448
Accuracy			0.97	900
Macro Avg	0.97	0.97	0.97	900
Weighted Avg	0.97	0.97	0.97	900

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The test results showed an accuracy of 0.97, with consistently high classification reports in both classes, including precision, recall, and F1-score, which ranged from 0.96 to 0.99. Several factors can explain this high performance. First, key numerical features such as price and quantity are directly related to revenue, thereby significantly contributing to class separation. Second, the stacking method leverages the relative strengths of each base model and optimizes them through a meta-learner, resulting in more stable and accurate predictions.
The metric distribution exhibits a symmetrical pattern: class 0 has a higher recall (0.99) than precision (0.96), whereas class 1 has the opposite, with higher precision (0.99) than recall (0.96). This indicates a balance in the decision threshold trade-off, where the model is more conservative in detecting all positives in class 1 but stricter in ensuring that those optimistic predictions are correct. This pattern demonstrates the model's consistency and accuracy in classification while also showing performance stability in both classes.

Fig. 8. Learning Curve of Stacking Ensemble

Figure 8 is a learning curve graph from a stacking ensemble, illustrating the consistency of model performance as the training data size increases. At the beginning of training, a significant difference exists between the training score and the validation score, indicating potential overfitting because the model has learned too specifically from the limited data. However, as the data increases, the difference narrows, and both scores converge toward an accuracy level of around 0.97–0.98.
This indicates that the model has low bias and controlled variance at larger data scales. The stability between the training score and validation score indicates that the model not only memorizes the training data but also recognizes relevant patterns in new data.
Therefore, this graph demonstrates that the stacking ensemble exhibits good generalization capabilities and does not encounter serious issues related to overfitting or underfitting at the given data size.

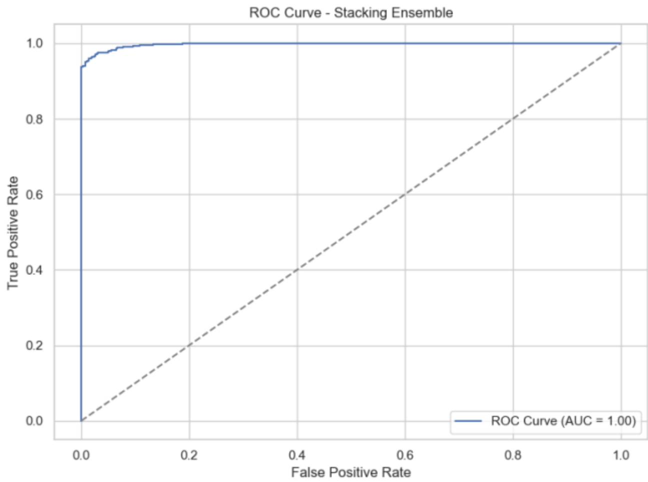

Fig. 9. ROC Curve of Stacking Ensemble

Figure 9 presents the ROC curve of the stacking ensemble, indicating that the model exhibits very high classification performance with an AUC value approaching 1.00. This indicates that the model can distinguish between positive and negative classes almost perfectly, as the curve approaches the upper left corner of the graph. The higher the AUC value, the lower the probability of classification errors between different classes.
The curve far above the baseline confirms that the model has high sensitivity without sacrificing specificity. In other words, the probability of the model correctly classifying the positive class is very high even though the data is balanced.
These findings demonstrate that the stacking ensemble approach effectively addresses the limitations of individual models by combining predictions, yielding stable and accurate classification performance. Therefore, the ROC curve reinforces the validity of the model's ability to generalize well on the test data.

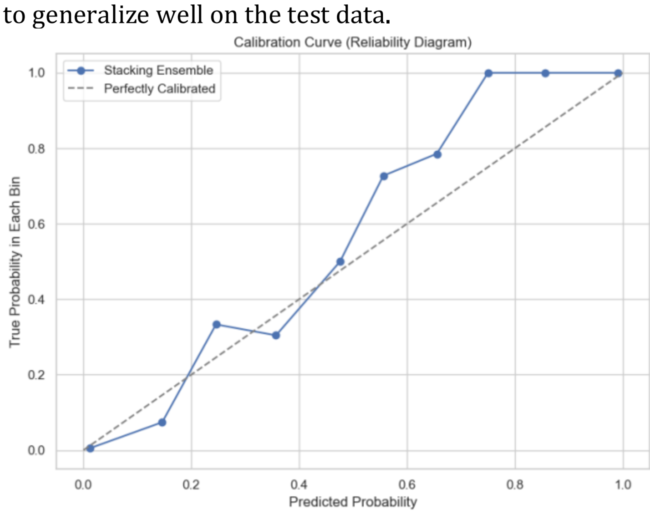

Fig. 10. Calibration Curve of Stacking Ensemble

Figure 10 is a calibration curve graph showing the degree of agreement between the probabilities predicted by the

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model and the actual probabilities. The graph shows that, although there is a slight deviation in low probabilities below 0.3, the model curve overall approaches the perfect calibration line. This indicates that the probabilities generated by the stacking ensemble are relatively well calibrated.

Probabilities that are close to perfect calibration are important because they provide more reliable interpretations in risk-based decision-making. For example, when the model predicts a probability of 0.8, the actual probability of a positive event is also close to 80%.

In other words, despite fluctuations in the moderate probability range, the model remains capable of producing consistent and valid probability estimates. This reinforces the practical value of the stacking ensemble not only as a classification model but also as a probability-based prediction tool applicable in real-world scenarios.

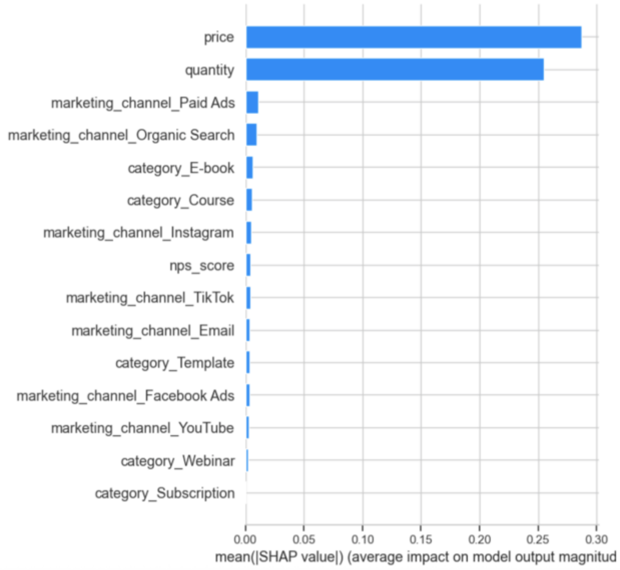

Fig. 11. Mean Absolute SHAP

Figure 11 is a graph of the average absolute results of model interpretation through SHAP analysis. These results indicate that price and quantity are the two most significant variables influencing the prediction. The average absolute SHAP values for these two features are consistently higher than those of other variables, indicating that price and product quantity are the primary factors influencing the model output. Other variables, such as marketing channels (e.g., Paid Ads, Organic Search) and product categories (e.g., E-books, Courses, Template_Category), show additional influence. However, their contributions are relatively minor and act as supporting factors. The summary plot (mean(|SHAP|)) highlights the importance of price and quantity at the global level, where both systematically influence prediction outcomes.

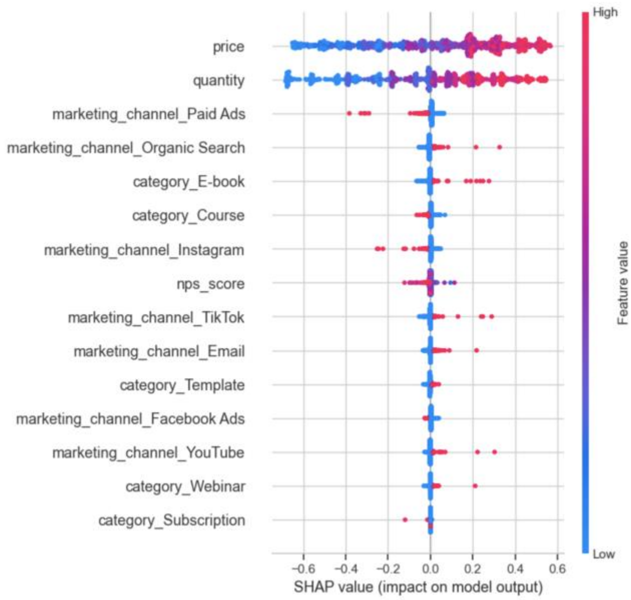

Fig. 12. Beeswarm Plot

Figure 12 is a beeswarm plot that provides a distribution perspective at the individual level, illustrating the variation in the impact of these two variables on model output. Specifically, high values for price tend to drive optimistic predictions, while low values for quantity are more frequently associated with negative impacts.

Strategically, these findings emphasize that the primary focus in formulating business policies and marketing strategies should be directed toward controlling pricing strategies and optimizing sales volume. Other variables, though not dominant, still hold value as competitive differentiators and can be used to enhance the effectiveness of marketing strategies. Therefore, this predictive model consistently places price and quantity as the core factors determining the success of predictions and the direction of business strategies.

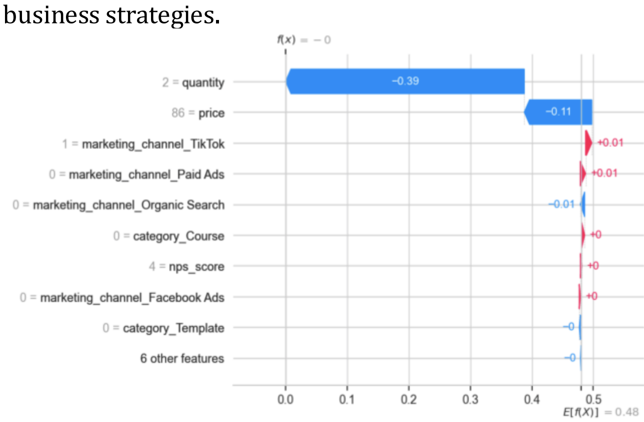

Fig. 13. Contribution of Features to Model Prediction

The results of the analysis using the SHAP method show that the contribution of features to model predictions is highly concentrated on core variables, as shown in Figure 13. Based on the graph, the model's global expected value is

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E[f(X)] = 0.48, with the final prediction result approaching zero.

The quantity feature is the primary determinant, with a SHAP value of –0.39, accounting for approximately 74% of the total contribution to the output. This is followed by a price contribution of –0.11, or approximately 21% of the model's total influence. Conversely, other variables, such as TikTok marketing channel, Paid Ads, and organic search, contribute ±2% each, with an inconsistent direction of impact and relatively small influence.

Overall, this analysis confirms that model predictions at the individual level are dominated by two main variables: quantity and price. Other factors, particularly digital marketing channels, play a secondary role with marginal contributions. The strategic implications of these findings underscore the need to prioritize decision-making in terms of price and product quantity management, as these two aspects have been proven to be the primary determinants shaping the model's output probability.

4.2. Discussions

Compared to previous studies, this research makes a significant contribution to the development of digital marketing prediction models by addressing various existing gaps. Our findings demonstrate that combining Stacking Ensemble with SHAP for interpretability can enhance prediction accuracy and provide greater transparency in understanding how features such as price and quantity influence revenue predictions.

One of the main gaps identified in previous studies, such as those conducted by Lin et al. (2020) and Asadi and Kazerooni (2024), is the lack of clarity in understanding which features are most significant in predicting user behavior, particularly regarding price and quantity [9], [11]. Although Lin et al. (2020) introduced the SE-stacking model, which successfully integrated multiple predictive models, the study failed to identify and highlight the key factors underlying the prediction results. Our research addresses this gap by integrating SHAP to determine feature importance, thereby facilitating more straightforward interpretation of how price and quantity directly influence revenue predictions. Thus, this study provides more actionable insights for marketers and business decision-makers who require transparency and understanding of the factors driving their digital marketing campaigns.

Another limitation in previous research, such as that conducted by Arboleda-Florez and Castro-Zuluaga (2023) on the SHAP method, is the lack of application to ensemble models that combine multiple predictive models. While their focus on SHAP aids in interpreting demand forecasts, the application of ensemble methods, such as Stacking Ensemble, has not been thoroughly explored in the context of digital marketing prediction [10]. In contrast, our research presents a unique application of Stacking Ensemble to enhance prediction accuracy while maintaining interpretability through SHAP. This approach effectively addresses the dual need for accurate predictions and actionable explanations in a business context.

Additionally, many studies focus on complex deep learning models, such as the Temporal Fusion Transformer (TFT) proposed by Würfel et al. (2021), which, while achieving high accuracy, require large datasets and significant computational resources [12]. Our research highlights the practical advantages of using more computationally efficient methods, such as Stacking Ensemble, which can achieve comparable predictive performance without requiring the substantial resources needed by deep learning models. This makes our approach more accessible for businesses with limited computational infrastructure.

Additionally, previous research, such as that conducted by Yaiprasert (2023), demonstrates the success of machine learning ensembles in marketing strategies; however, it does not explicitly address the challenges of overfitting and computational costs in large-scale applications [13]. This study addresses these issues by using cross-validation and parallel processing, which not only reduces the risk of overfitting but also enhances computational efficiency.

Finally, while many studies focus on improving accuracy, the interpretability of results often receives insufficient attention. Our research, by integrating SHAP, ensures that predictions are not only accurate but also transparent. This aspect is crucial in the application of machine learning models in business, where understanding the underlying factors of predictions can drive better decision-making and strategy development.

This research represents a significant step forward in improving the transparency, accuracy, and practical application of machine learning models in digital marketing. By combining Stacking Ensemble with SHAP, we provide a model that not only improves revenue predictions but also provides clear insights into the key factors influencing those predictions, such as price and quantity. This contribution addresses several important gaps identified in previous research, paving the way for more effective and easily interpretable marketing strategies.

5. CONCLUSIONS

This study aims to develop an effective and interpretable prediction model in the context of digital marketing, focusing on factors that influence digital transaction revenue, such as price and quantity. The main contribution of this study lies in the application of the Stacking Ensemble approach, combined with interpretable artificial intelligence (XAI) methods using SHAP, to provide a more transparent interpretation of the variables' contributions to prediction results.

The main findings of this study indicate that the Stacking Ensemble model, which combines several base models, including Logistic Regression, Gaussian Naïve Bayes, SGDClassifier, and Support Vector Classifier, achieves a

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prediction accuracy of 97%. Based on evaluations using various metrics, such as precision, recall, and F1-score, this model demonstrates excellent performance with values ranging from 0.96 to 0.99 for both classes. Additionally, learning curve and ROC curve analyses confirm that this model exhibits good generalization capabilities, unaffected by overfitting, and achieves an AUC close to 1.00, indicating nearly perfect classification capabilities.

The implications of this research for the business world, particularly in digital marketing, are significant. The proposed model offers a clearer understanding of the factors influencing purchasing decisions, including price and quantity. These findings enable businesses to optimize their pricing strategies and sales volume, thereby increasing revenue. The use of SHAP in interpreting model results also provides greater transparency, enabling decision-makers to clearly understand the reasons behind the generated predictions, thereby increasing trust in the model and reducing uncertainty in data-driven decision-making.

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