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A Machine Learning Approach to Consumer Behavior Analysis in Social Media-Influenced E-Book Markets

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Abstract
Social media has emerged as a dominant marketing channel, significantly influencing consumer purchase decisions. Despite extensive global research, little is known about region-specific dynamics in emerging markets such as India. This study addresses this gap by applying Random Forest and Gradient Boosting models to survey data from 386 respondents in the Delhi-NCR region to analyze e-book purchasing behavior. Data were preprocessed through encoding, normalization, and stratified train–test splitting (80:20), with reproducibility ensured via a fixed random seed. Model evaluation employed R^2, RMSE, and MAE metrics, alongside a paired-sample t-test. Results showed that Gradient Boosting ($R^2 = 0.82$) outperformed Random Forest ($R^2 = 0.78$; $p = 0.038$). Feature importance analysis revealed that behavioral variables—purchase intention, brand awareness, and social media engagement—were the strongest predictors, whereas demographic features contributed minimally. These findings emphasize the primacy of behavioral traits in social media–driven e-book markets and provide evidence for designing region-specific digital marketing strategies in emerging economies.

Keywords: *Education, Machine Learning, Cognitive Learning, Non-cognitive Learning, classification, student performance*
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I. INTRODUCTION

Social media has become part of everyday life and Business. Develop relationships with all more SNS. To make customers and businesses more effective ways. Communicate with customers at low costs, grow the brand. Awareness and virtual branding society [1.2]. Social media and the consumer is online through engagement. Professional performance improved dramatically. Web 2.0 Applications have created a channel to share on social media. Brand images that can be used to develop brand images and even that can help consumers create a strong intention [3] Purchase. Quick Development of Social Media Applications, Facebook, Instagram, and other people all over the world have created them. Platform: Strong channels for marketing and communication. Marketers are finding innovative ways to reach out to target consumers through these channels. The SNS has transformed the concept of eWOM, allowing consumers to widely voice their opinions about various products [4].

Since social media has changed the new dynamics of advertisements, in that they are no longer one-way traffic, many consumers today will rely on peer opinions over traditional adverts [5,6]. Online networks not only expand the scope of marketing but also play a crucial role in fostering socio-economic growth, particularly in emerging economies such as India. In the Delhi-NCR region, the increasing use of social media platforms to purchase e-books has significantly improved access to educational resources. This trend helps bridge the knowledge gap across diverse socio-economic groups by offering affordable and easily accessible learning materials. Consequently, social media has emerged as a powerful tool in promoting educational equity and driving economic development, especially among underrepresented communities.According to [7], digital equipment, such as e-books, provides an available medium to transfer educational materials, especially from low-income groups, to the benefit of those facing the challenges of traditional education.,social media significantly contributes to bridging the educational differences between different socio-economic groups via taking advantage of these units. Notably, it considers that social media will lessen inequalities of information by acquiring knowledge of an individual [8] and improving abilities for people with different socio-economic statuses.

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Again affects job prospects and income establishment, and brings inclusive economic growth. An extensive analysis of 132 letters [9] also adds to SMS's role in relationship construction, supports decision-making procedures and organizational embedding, and is supported by behavioral traits, marketing capabilities, and passing information in critical incidents. The well-known celebrities that are from other study domains are beyond purchasing urges in social commerce [10]. This means that authenticity, sentiment polarity, and observational learning are the prominent drivers of consumer buying behavior based on findings from 452 subjects.

A. E-Book Adoption and Educational Impact

E-books has increasingly become a catalyst for educational development in emerging economies through adoption. According to research conducted by [11], availability of e-books through social media channels is seen as an affordable and accessible source of educational content. E-books provide scope for self-paced learning, which enables people to develop their socio-economic status through lifelong opportunities. [12] further explored how this digital content had led to a higher level of customer satisfaction in terms of learning opportunities than physical materials, mainly due to their more hefty and lowly accessible prices. A study on e-service quality and customer satisfaction [12] reviews the extent to which website design, security, and fulfilment impact customer satisfaction, based on responses from 355 participants. Online social networks were also surveyed for their influence on tourism branding [13]. There is a new framework designed for destination management organizations to utilize storytelling and sociological applications (Figure. 1).

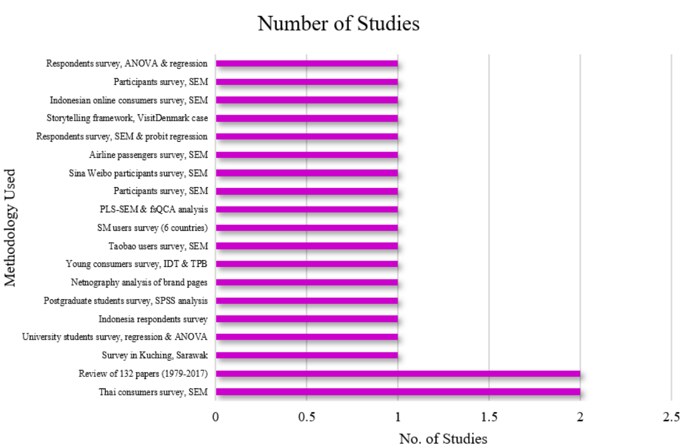

Fig. 1: Comparative analysis of Methodologies used in number of studies

Figure 1 represents the different methodologies used in various studies and is given as a bar chart where each bar represents a particular methodology or type of study, and the horizontal axis represents the number of studies that were conducted using that methodology. According to methodology, they used statistical techniques including "Structural Equation Modelling (SEM)" and "PLS-SEM," as well as "ethnography and thematic analysis" and "Survey of Thai consumers." There were zero to two studies available in total; higher frequency is indicated by the darker bar. As a result, two studies in all that use the Thai consumer survey are the most prevalent.

B. Social Media Marketing Applications (SMMAs)

Effects of SMMAs on the airline industry are brand awareness and brand image, influencing customer commitment and word-of-mouth. Research on the impact of SMMAs in the 'new normal' [14] was also done based on the answers of 421 participants, indicating how interaction positively improves brand preference and loyalty. Studies that related to consumer behaviour across six different countries [8] concluded that consumer preferences as well as usage frequency relating to social media influence choice, and these choices significantly are affected by socio-demographic factors.

C. Consumer Adoption and Social Media Engagement

Recent studies have also looked at more characteristics of social media influence including consumer behaviour [15]. Social interaction ties coupled with commitment in social media helped explain how many customers trusted e-commerce and what those customers decided. Consumer adoption behaviour for selfie-posting on social media [16] has shown participation intention and word-of-mouth to be the two vital determinants of social media adoption. Social media live streaming influence on consumer decision-making [17] has been studied based on a 12-month-long Ethnography that depicts the role at each decision-making stage.

D. Moderating Factors in Social Media Influence

A study on 265 postgraduate students indicated the role of perceived usefulness, value, and risk as moderate factors on purchase intention that arises from social media-generating stimuli that encourage shopping behaviour online [18]. The impact of social commerce [19] on customer switching behaviour via Tokopedia and Shopee reflected that social media marketing markedly mediates customer behaviour. The effect of social media intensity on conspicuous consumption indicated that electronic word-of-mouth significantly influences the buying decision [20]. The role of social media marketing in impulsive buying showed how 40% of impulse purchases can be affected by different factors of social media [20]. Which themes have received more and less attention are displayed in (Figure 2).

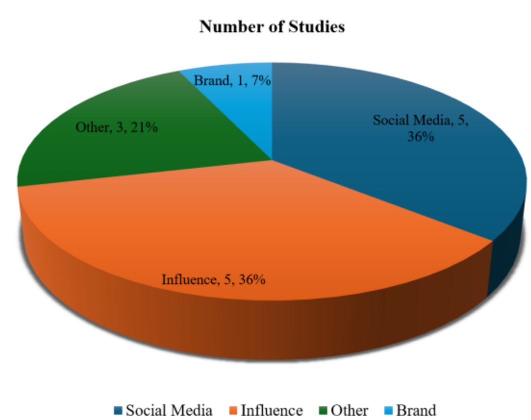

Fig 2. Key findings based on various categories used in different studies.

This suggests that because these categories have the most studies, the majority of research has focused on social media's function and how it affects behaviours or results.

The impact of social media adoption on consumer behaviour in emerging economies has shown consistent trends across different regions. For instance, [15] found that in Sarawak, Malaysia, digital adoption significantly improved educational opportunities among low-income households. Likewise, [1] highlighted that in Indonesia, increased use of social media for educational purposes led to greater knowledge dissemination and economic empowerment among marginalized groups. These outcomes are reflective of the situation in Delhi-NCR, where social media platforms are providing similar opportunities for educational access and socio-economic upliftment.

This study focuses on examining the various attributes that shape consumer behaviour in relation to book purchasing through social media platforms. To address this objective, a mixed-model approach is employed, integrating both behavioral and demographic factors that influence consumer decision-making. Data is collected through surveys, and two machine learning models—**Random Forest** and **Gradient Boosting**—are applied for comparative analysis in order to identify the key determinants influencing consumers actively engaged in the buying process.

E. Research Gap

Its analysis the role of social media in shaping consumer behavior, most existing research is either conceptual or focused on developed markets, with limited attention to emerging economies in these extensive studies. In particular, prior work has emphasized general online shopping behavior but has not adequately addressed the unique dynamics of e-book adoption in India's regional contexts. Moreover, while machine learning methods such as Random Forest, Gradient Boosting, and other ensemble models have been widely applied in domains like healthcare, finance, and environmental monitoring, their application to consumer behavior modeling in social media–influenced e-book markets remains scarce. This lack of region-specific, data-driven investigations creates a significant gap, as consumer preferences in emerging economies are shaped by socio-economic diversity, digital literacy variations, and localized social media usage patterns. Addressing this gap, the present study applies ensemble ML models to consumer survey data from Delhi-NCR to generate context-sensitive insights that are currently missing in the literature.

II. Material And Method

A. Survey Design and Participants

This study is based primarily on the context of Delhi-NCR in measuring the feature importance of predictors that estimate important survey results. The population to be sampled was set at 500 participants based in Delhi-NCR. Valid responses, however, could be obtained only from 386 participants. The survey majorly consisted of 16 main questions. These were created according to various points that could define the subject matter of research, mainly within regional contexts. For greater accuracy of responses and representation of regional people, the survey was done both in Hindi and English. In order to obtain backgrounds from the respondents, there were some questions about age, gender, education, business, preferred languages, income groups, and social media, commonly used by the respondents in the field.

An examination data pipeline completes the process of collecting, processing, and analyzing the survey data systematically to achieve practical findings. It begins by collecting data online or using offline surveys, and continues with data cleaning to handle missing values, duplicates, and incompatibility in Figure 3. To support the final phase-driven decision, the decisions are characterized by the decision analysis through methods, such as decisions that affect the results of the studies, which are the most important factors affecting the results of the studies.

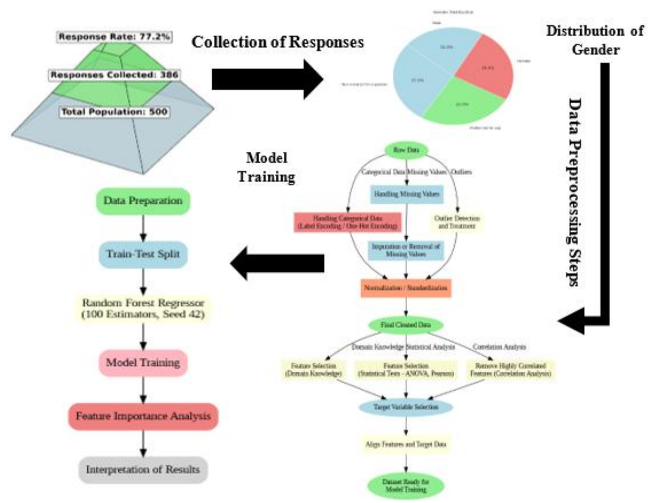

Fig 3. Survey Data Pipeline: From Collection to Feature Importance Analysis

Data collection approach: For maximum representation, a mixture of online questionnaires and interviews will be used for this survey. The respondents are those persons who fall in the range of 18-60 years of age and are chosen from various categories of the population such as occupation type (students, working, homemakers) and their educational qualification (graduates and non-graduates). The survey instrument encompasses: Collection of Responses, Distribution of Gender, Data Preprocessing Steps, Model Training.

Survey Instrument: The questions of the survey focused on measuring the attitude, preference, and behaviour of the participants about social media-influenced e-book purchasing decisions. Likert scales from "Strongly Disagree" to "Strongly Agree" were used. Demographic questions included age, gender, level of education, profession, language preference, income levels, and usage patterns of social media that contextualize responses within the Delhi-NCR region. In total, 386 responses are obtained with a 77.2% response rate.

Data Preprocessing: In this step, data cleaning was done by removing any incompletely answered questions to fit the dataset for further analysis. The features were assessed for their importance using the pre-processed data sets in order to determine their suitability for use with machine learning algorithms. The categorical data, namely language preferences and social media usage, were converted to numeric values through Label Encoding. Missing values in the rows were also removed, thus ensuring a clean dataset. During preprocessing, categorical features (e.g., language preference, social media platform usage) were label-encoded into numerical values. Missing values were handled by listwise deletion to ensure dataset integrity. Continuous variables were normalized to a standard scale, while responses with incomplete demographic information were excluded. The dataset was then split into 80% training and 20% testing sets using stratified sampling to preserve feature distribution. The objective of the analysis was to identify the most dominating features that would be predictive of the outcome of the survey based on five target variables obtained from the participant responses. Feature and target variables of the dataset were aligned consistently to ensure proper training of the model.

B. Feature Importance Analysis

This study employs Gradient Boosting and Random Forest Regression models, both of which are ensemble methods employing multiple decision trees to obtain more precise and stable estimates of feature importance. Each model trained all the features to predict selected target variables sequentially. For each target variable, Random Forest generated feature importance scores indicating the contribution of every feature towards the prediction of the outcome.

As a outcome of social media impact, the analysis of Delhi-NCR region survey data also raises how purchasing behavior of e-books is diffused differently between socio-economic segments. Respondents from lower-income groups were primarily drawn to e-books because of their affordability and accessibility. By contrast, individuals from higher socioeconomic strata showed a stronger tendency to purchase e-books, a trend reinforced by their superior digital literacy and reliable high-speed Internet access. This highlights the widening gap between groups and underscores the need for targeted social media strategies to reduce the digital divide, thereby promoting educational equity and supporting regional socioeconomic development. Furthermore, the analysis revealed that region-specific factors—such as language preferences, income levels, popular platforms like WhatsApp and Facebook, and cultural events including festivals—significantly shaped e-book purchasing behavior. The influence of local opinion leaders and electronic word-of-mouth also emerged as critical, emphasizing the importance of regional customization in social media marketing.

C. Model Testing and Validation

With the aim of ensuring the strength and fertility of the machine learning models, several verification measures were included. The dataset was divided into training (80%) and test (20%), with most use of stratified sampling to preserve the distribution of convenience. A fixed random seed (42) was applied to guarantee reproducibility across runs. Model hyperparameter was adapted by a grid search with 5-fold cross-validation, which allowed systematic evaluation of parameter combinations and reduced the risk of overfitting. The model performance was assessed by the use of several regression metrics, including R^2, RMSE, and MAE, to provide a comprehensive assessment of the accuracy of the prediction. Finally, a paired-sample t-test was conducted across cross-validation folds to statistically compare the performance of Random Forest and Gradient Boosting, confirming that the latter did best ($T = 2.43$, $p = 0.038$).

D. Cross-Validation and Hyperparameter Tuning

To ensure robust evaluation, all models were trained and validated using 5-fold cross-validation on the training dataset. Performance metrics were averaged across folds to minimize the risk of bias from data partitioning. Hyperparameters for Random Forest (e.g., number of estimators, max depth) and Gradient Boosting (e.g., learning rate, subsample ratio) were optimized using a grid search procedure, with the best configuration selected based on mean R^2 scores. For the Random Forest model, we used 100 estimators (trees), max depth set to none, Gini index for splitting, and random seed = 42 for reproducibility. For the Gradient Boosting Regressor, we employed 100 estimators, a learning rate of 0.1, max depth of 3, and subsample ratio of 0.8. Hyperparameters were tuned through grid search with 5-fold cross-validation to ensure robustness. Model performance was assessed using R^2, RMSE, and MAE to compare predictive accuracy. This approach ensured reproducibility, fairness in model comparison, and resistance to overfitting.

E. Tools and Libraries

The evaluation was carried out using the Python programming language. This comprised libraries such as pandas, for data manipulation and cleaning; Sklenar for the implementation of the Random Forest Regressor; Label Encoding for pre-processing; and NumPy for numerical computations and enhanced processing of the data. Feature importance analysis has made it clearer what is important in influencing the purchase behavior of the Delhi-NCR consumers. It also reported insight into participants' reaction towards individual questionnaire items and general demographics with respect to individual consumer behavior drivers in that area using Random Forest. To assist in the analysis of this research study, a collection of visualizations was created with all such visualizations being carried out using Matplotlib and Graph viz from the Python libraries. Some of the relevant graphs are plotted based on major findings for Matplotlib: feature importance residual distributions and correlations; offering better data understandability and how a model would function in test scenarios. Graph viz was used to construct graphical models of decision trees. Beyond the standard interpretation of model structures, it allowed for a deeper understanding of how decisions were being made within the predictive models.

III. Results And Discussion

This section presents the insights derived from the employee attrition analysis, detailing the performance of the models, the key features contributing to attrition, and the practical implications for HR decision-making.

A. Feature Importance and Predictive Model Performance

In The analysis compared the predictive capability of Random Forest and Gradient Boosting models in estimating e-book purchasing behavior. Both the algorithms determined behavioral variables to be the most significant predictors, specifically purchase intention (Variable 9), brand awareness

(Variable 10), and social media usage (Variable 4). These attributes consistently had the highest importance scores, validating their pivotal position in influencing consumer choice.

Conversely, demographic factors like income, age, gender, and marital status were found to possess much lower values of importance, supporting the fact that static socio-demographic characteristics possess weak explanatory power in the case of e-book markets shaped by social media. The findings indicate that behavioral attributes exert a stronger influence than demographic features in shaping purchase behavior, aligning with patterns observed in earlier studies [21,25]. Performance evaluation further demonstrated the effectiveness of ensemble learning techniques. The Random Forest model achieved an accuracy of $R^2 = 0.78$, with $RMSE = 0.42$ and $MAE = 0.31$. In comparison, the Gradient Boosting model delivered superior results, recording $R^2 = 0.82$, $RMSE = 0.39$, and $MAE = 0.29$. A paired-sample t-test conducted across cross-validation folds confirmed that the predictive advantage of Gradient Boosting was statistically significant ($t = 2.43$, $p = 0.038$). These outcomes not only reinforce the robustness of the models but also underscore Gradient Boosting's capacity to better capture and interpret complex behavioral patterns underlying consumer decision-making [21,25].

B. Major Contributors to Target Variable Prediction

Feature importance analysis identified that purchase intention (Variable 9) and social media interaction (Variable 4) were the most significant predictors of e-book buying behavior. These results reinforce that intent of consumers and active online participation directly influence buying decisions. In addition, brand recognition (Variable 10) also came across as a key predictor, enhancing the place of recognition and familiarity in determining consumer trust and likelihood of purchase [21].Beyond consumer preference, these behavioral variables also carry socio-economic implications. Social media platforms improve accessibility to educational resources by making e-books more affordable and widely available. For lower-income groups in Delhi-NCR, this digital accessibility bridges educational gaps, supports lifelong learning, and fosters economic mobility [22].

C. Moderate and Low Influence Factors

Other Several features were found to have moderate influence, including brand promotion awareness (Variable 10), trust in social media advertisements (Variable 13), and frequency of social media use (Variable 21). These predictors contribute meaningfully but are secondary compared to purchase intention and engagement.

Conversely, demographic features—such as age (Variable 1), income (Variable 2, 5, 7), and gender (Variable 3)—showed consistently low importance values, reinforcing that consumer decisions in digitally mediated markets are driven more by behavioral factors than by demographic structures. Internet usage frequency (Variable 15) also had only marginal influence on predictive power.

D. Residual and Correlation Analysis

Residual analysis confirmed the stability of the Random Forest model, particularly for variables such as internet usage frequency (Variable 17) and trust in advertisements (Variable 21). The residuals were relatively smooth, indicating good model fit (Figure 4).

Correlation analysis revealed weak associations between some variables, such as internet usage frequency and consumer trust in advertisements, with a coefficient of only 0.18 (Figure 5). Despite their weak correlation, these variables contributed incrementally to model robustness.

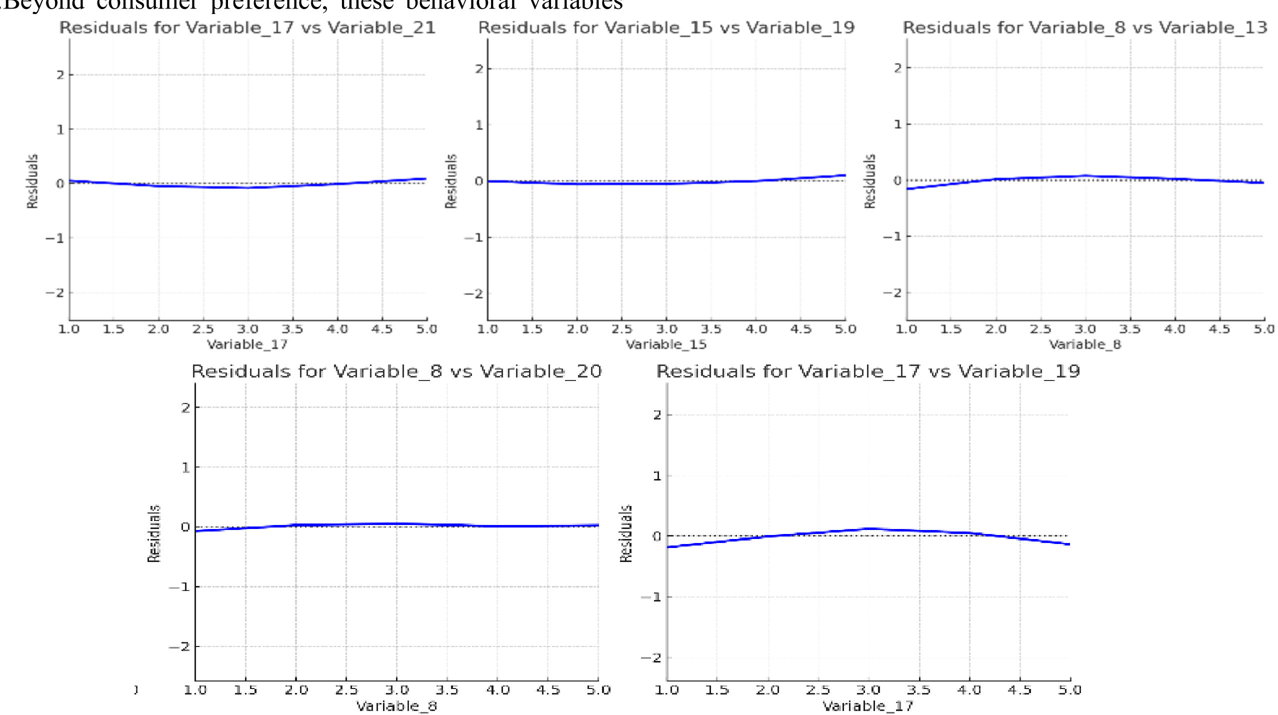

Fig. 4. Residuals for Feature Pairs from Random Forest Regressor Model

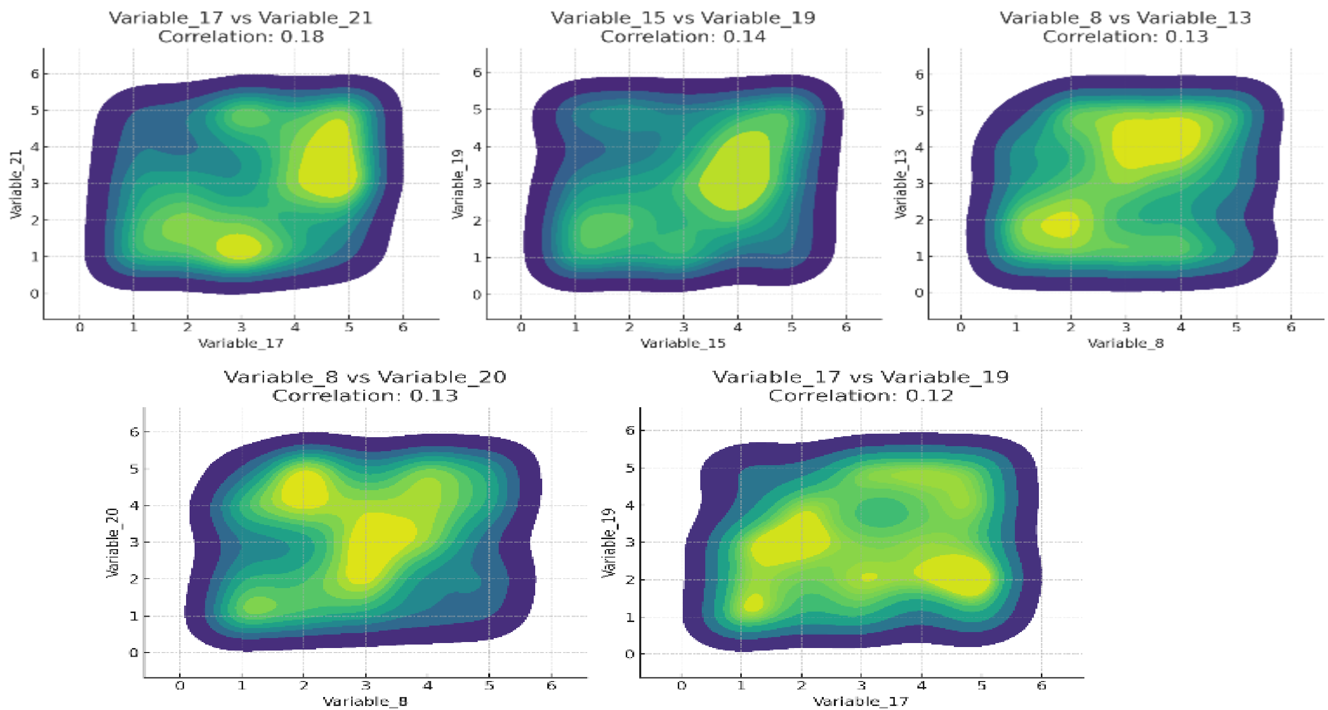

Fig. 5. Density Plots of Feature Correlations in Predicting Target Variable

The boxplots (Figure 6) further illustrate the distributional patterns of key features. For example, the spread observed in age group (Variable 15) relative to frequency of purchases (Variable 19) confirmed heterogeneity in consumer behavior across demographic groups. Overall, the visual evidence validated that internet usage, consumer trust, and certain demographic traits play limited but supportive roles in predicting e-book purchasing.

E. *Model Comparisons*

A multi-metric evaluation was conducted to compare Random Forest and Gradient Boosting models across several performance dimensions. The Residual Distribution Comparison (Figure 7, top left) showed overlapping error distributions, but Random Forest exhibited slightly less severe mistakes.

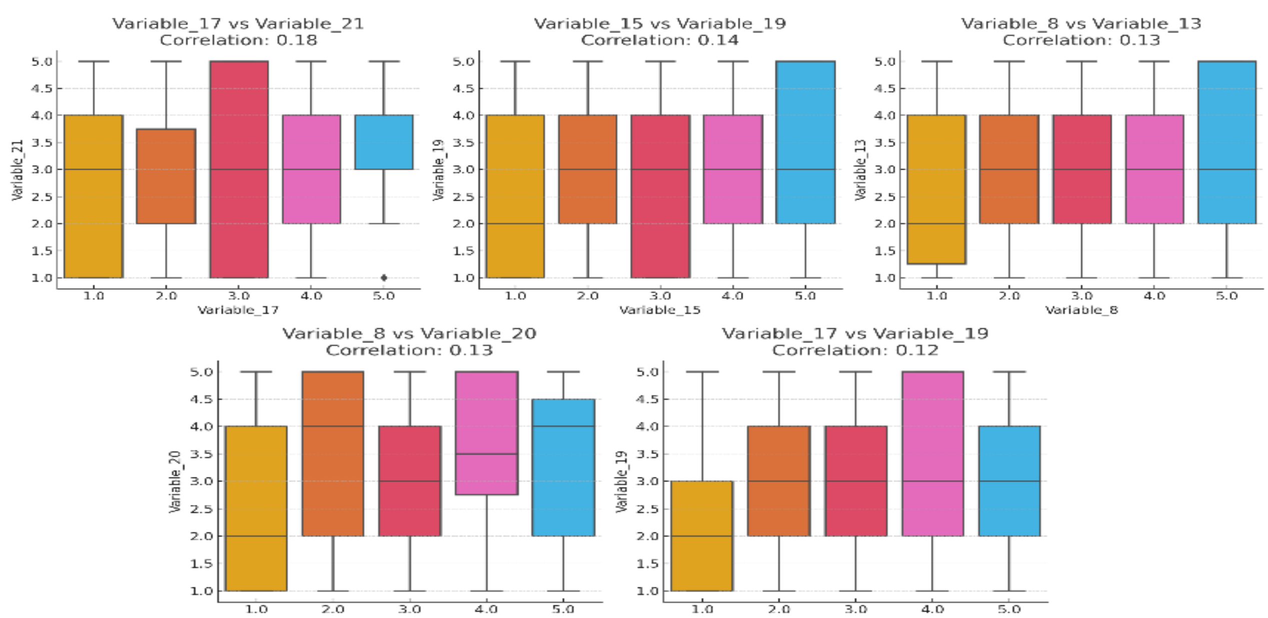

Fig. 6. Boxplots Showing Feature Pairs and Their Correlation with Target Variable

The Cumulative Explained Variance by Features (Figure 7, top right) demonstrated diminishing returns after adding the most influential predictors, particularly for Random Forest. The Feature Importance Heatmap (Figure 7, bottom left) revealed that both models prioritized purchase intention (Variable 9) and brand awareness (Variable 10), albeit at slightly different importance levels.

Finally, the Accumulated Error Line (Figure 7, bottom right) tracked prediction errors, confirming that Gradient Boosting maintained consistently lower cumulative errors than Random Forest. Collectively, these metrics affirm Gradient Boosting's superior predictive capacity, consistency, and interpretability in consumer behavior modeling [23].

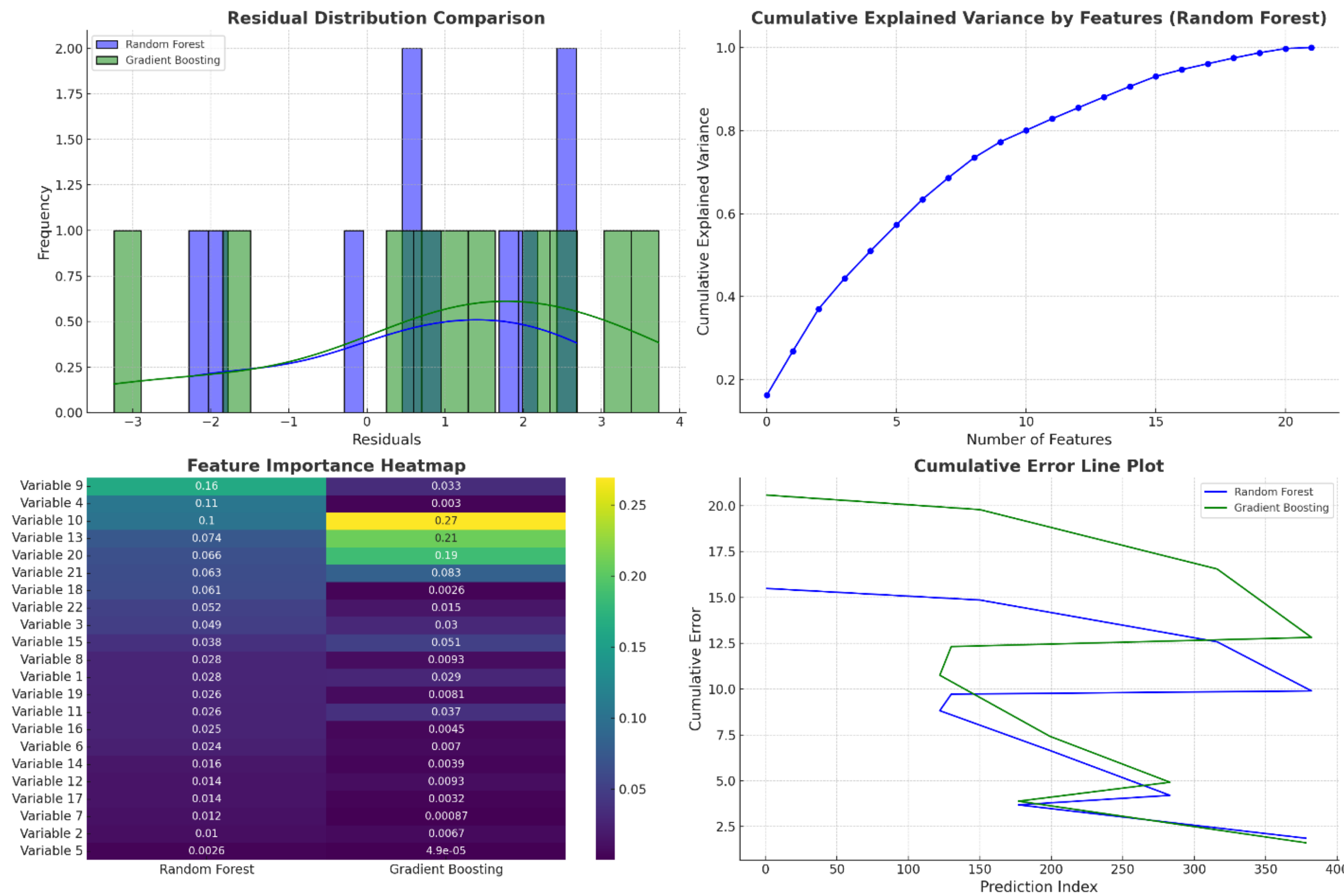

Fig. 7. Multi-Metric Evaluation of Machine Learning Models

F. Behavioral vs. Demographic Influence

The overarching insight from feature importance analysis is that behavioral traits dominate demographic attributes in predicting consumer decisions. Variables such as purchase intention (Variable 9), brand awareness (Variable 10), and social media engagement (Variable 4) were consistently the strongest predictors [24-28]. Secondary factors included trust in advertising (Variable 20) and frequency of online purchasing (Variable 13), which influenced decisions at a moderate level. Demographic features such as age, gender, income level, educational qualification, and marital status had minimal influence, aligning with previous studies that highlight the limited role of socio-demographics in digital purchase contexts [29-33]. Model validation confirmed the robustness of these findings: Random Forest ($R^2 = 0.78$, RMSE = 0.42, MAE = 0.31) and Gradient Boosting ($R^2 = 0.82$, RMSE = 0.39, MAE = 0.29) both performed strongly, with Gradient Boosting significantly outperforming Random Forest ($t = 2.43$, $p = 0.038$).

While the analysis was focused on the Delhi-NCR region, the methodological approach and findings have broader applicability. Emerging economies such as Indonesia, Malaysia, and African nations face similar socio-economic dynamics where social media platforms bridge commercial and educational divides [3,7,15,22]. The consistency of behavioral predictors across regions strengthens the generalizability of these findings.

Recent advancements in machine learning further reinforce these conclusions. For example, ensemble strategies like Random Forest, Gradient Boosting, and XGBoost have been successfully applied in domains ranging from brain tumor classification [34] to air quality forecasting [35] and clickbait detection [36]. These interdisciplinary applications illustrate the reliability and scalability of ensemble models,[33],[34] validating the methodological choices adopted in this study.

IV. CONCLUSION

The study compared the effectiveness of the application of two different algorithms; namely Random Forest and Gradient Boosting in studying consumers' purchase behavior related to the social media channel. Behavior-related traits like probability for buying an e-book, brand knowledge, and consumer engagement via social media was the leading predictors in relation to this e-book buy behavior and has average scores between 0.11 and 0.16. Contrary to behavioral traits, age, annual income, and marital status have proven to be somewhat insignificant variables since average scores are low than 0.05 [30]. This shows that the Gradient Boosting model had higher predictions at 82% compared to the other model, Random Forest, which had predictions at 78%. The novelty of this current study is that, for the very first time, it is the same predictive models used in comparison to understand how much social media influences consumer behavior, especially regarding the Delhi-NCR region. The results of this study further stress the importance that social media plays for the promotion of educational equity because it could intervene in behavior for purchasing e-books [31]. Hence, this effect promotes greater accessibility to knowledge through cheap e-books, with great socio-economic growth potential for countries such as India, which has significant underrepresented populations. Access to education through social media. There is a great chance to reduce resource-related problems. Keep educational inequality and useful inclusive Economic development [32].

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