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Culturally Adaptive Financial Product Personalization: A Machine Learning and Uplift Modeling Framework for Multicultural Markets

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ABSTRACT

Digital marketing strategies often fail to account for cultural differences in consumer responses, particularly when engagement and conversion behaviors are evaluated separately. This study proposes a culturally adaptive analytics framework that integrates machine learning (ML), funnel-based modeling, and uplift analysis to examine marketing effectiveness across multicultural markets. A synthetic dataset containing 100,000 consumer–campaign interactions from nine countries was constructed by incorporating demographic characteristics, behavioral indicators, campaign attributes, and Hofstede-based cultural features. Logistic regression, random forest, and Light Gradient Boosting Machine (LightGBM) models were first employed to predict consumer engagement and conversion outcomes. A funnel-based approach was then introduced to separate click behavior from post-click conversion, while a Double-Robust (DR) Learner was applied to estimate the incremental effects of alternative marketing treatments. The results show that funnel modeling improved top-ranked targeting precision, increasing Precision@1% from 2.2% to 3.6% compared with direct conversion prediction. Uplift analysis further revealed heterogeneous treatment effects, with Short Message Service (SMS) campaigns showing approximately 2 percentage points higher incremental conversion gains than email campaigns in selected segments. Cultural alignment and consumer sentiment were identified as important factors influencing campaign effectiveness. Since the experiments are based on synthetically generated data, the findings demonstrate methodological feasibility rather than validated real-world marketing effects. Future studies should evaluate the framework using empirical campaign datasets with individual-level cultural information.

1. INTRODUCTION

Rapid globalization of markets has created outstanding opportunities and challenges for digital brands. As brands increasingly operate across national borders, understanding how cultural factors shape consumer engagement has become central to the success of international marketing campaigns [1]. In multicultural environments, consumers do not respond only to price or product quality; their decisions are also shaped by cultural norms, values, communication styles, and emotional cues [2]. Digital marketing strategies that fail to account for these differences often suffer from reduced efficiency, underscoring the need for culturally adaptive approaches.

Current research has investigated cultural effects in marketing through the cultural dimensions of Hofstede, such as frameworks that emphasize individualism, collectivity, uncertainty, and the role of long-term orientation in the design of consumer behavior. While these studies provide valuable theoretical insight, their translation is limited to practical, data-driven strategies [3, 4]. Most functions depend on descriptive analyses or traditional machine learning (ML) techniques that predict consumer reactions in general, often in different cultural contexts, and the step-by-step effects of specific channels, tone, or campaign design in different cultural contexts [5]. Moreover, conventional models typically treat the consumer journey as a one-step process, conflating engagement (e.g., clicks) with actual conversion behavior.

To address these gaps, this study introduces a novel methodological framework that integrates ML, funnel modeling, and uplift estimation for the systematic evaluation of culturally tailored marketing strategies. Funnel-based modeling separates the consumer journey into click probability and post-click conversion probability, offering a more realistic representation of decision-making [6]. Uplift modeling, implemented through the Double-Robust (DR)-Learner, quantifies the incremental impact of marketing treatments, allowing us to move beyond accuracy-based evaluation to assess causal effects [7, 8]. By combining these innovations with a culturally enriched dataset, our approach captures not only whether consumers respond, but also why and for whom specific strategies are effective.

Cultural factors play a pivotal role in shaping consumer perceptions, trust, and purchase decisions in global digital markets. Prior research highlights values, beliefs, language, religion, and material culture as key drivers of consumer behavior, emphasizing the importance of culturally adaptive marketing strategies for enhancing brand relevance and loyalty [9, 10].

Recent studies have integrated ML into digital marketing to model customer intent, predict conversions, and optimize campaign delivery in real time [11]. Algorithms such as gradient boosting, recurrent neural networks, and deep learning have shown effectiveness in segmenting diverse audiences and personalizing communication, though challenges remain in data integration, bias, and transparency [12, 13].

Cultural intelligence (CQ) has emerged as another critical capability, enabling firms to align strategies with local values. Research demonstrates that CQ, combined with social media and digital platforms, strengthens international marketing capabilities and improves performance in turbulent environments [14-16]. Parallel work explores AI-driven cultural adaptation, such as culturally sensitive natural language processing (NLP), recommender systems, and adaptive learning models, underscoring both opportunities and risks—including algorithmic bias and ethical concerns [17, 18].

Despite these advances, most prior works remain either descriptive or technology-centric, with limited integration of cultural frameworks and causal ML techniques for campaign optimization [19, 20]. Studies often conflate engagement with conversion and rarely quantify incremental effects of treatments across cultural contexts. This gap highlights the need for a comprehensive, data-driven framework that combines ML with uplift modeling to capture both predictive accuracy and causal cultural impact. Recent work in causal ML and AI-driven personalization has begun to address parts of this gap: for example, studies combining metaheuristic optimization with cultural factors in digital marketing [15], research on AI-driven personalization and consumer trust [7], and reviews of AI applications in advertising and targeting [12] each speak to elements of the problem addressed here. However, none of these combines funnel-based engagement/conversion decomposition with DR uplift estimation over an explicit Hofstede-based cultural feature set. This is the gap that the current study addresses.

This paper makes three contributions. First, it demonstrates the predictive and explanatory power of including cultural features such as sentiment, tone, and alignment indices into sophisticated ML pipelines. Second, it shows the power of funnel modeling in enhancing targeting accuracy through an explicit separation of engagement and conversion. Third, the uplift modeling emphasizes the strategic importance of designing the campaign. It demonstrates how the campaign result differs across country, channel, and tone, which allows useful information for resource allocation. The research thus provides a theoretical framework for cultural adaptation, with practical implications for the optimization of digital marketing.

2. METHODOLOGY

The study presents a comprehensive framework for analyzing and adapting digital marketing strategies in a multicultural environment by integrating functional ML, NLP, funnel modeling, and regression analysis to forecast campaign outcomes for culturally diverse consumer groups. It employs a synthetic multicultural dataset of 100,000 consumer interaction records across nine countries, incorporating demographic variables, campaign attributes, Hofstede's cultural dimensions, and behavioral outcomes such as impressions, click-throughs, and conversions. Data enrichment through sentiment analysis and topic clustering captures latent consumer attitudes, while cultural alignment indices highlight cross-national differences, ensuring both scale and realism in reflecting cultural heterogeneity. The methodology consists of three integrated components: baseline predictive modeling using logistic regression, random forest, and Light Gradient Boosting Machine (LightGBM) to benchmark engagement and conversion prediction; funnel modeling that conceptualizes consumer response as a two-stage process (click-through followed by conversion) to estimate conditional probabilities more precisely; and uplift modeling using a DR-Learner to quantify the incremental impact of strategies such as Short Message Service (SMS) versus Email or Family tone versus Discount tone across cultural subgroups. Evaluation combined predictive and causal metrics, with Receiver Operating Characteristic Area Under the Curve (ROC-AUC), Precision-Recall Area Under the Curve (PR-AUC), and Precision@k assessing predictive performance, while Qini curves, area under the uplift curve (AUUC), and Top-k uplift measured causal effectiveness. To enhance interpretability, feature importance plots and a country × channel uplift heatmap were generated to illustrate how cultural heterogeneity moderates campaign outcomes. By unifying funnel dynamics, cultural properties, and regeneration estimates, the framework provides a scalable, data-driven, and culturally adaptive approach to optimizing digital marketing strategies.

Figure 1 shows the functioning pipeline used in the study. This process begins with data collection, which includes demographic, behavioral, campaign, and cultural characteristics in a dataset. The next stage includes baseline predictive modeling (logistic regression, random forest, and LightGBM) to benchmark engagement and conversion prediction. The framework then advances to funnel modeling, where engagement and conversion are modeled sequentially to improve targeting precision. Finally, uplift modeling is applied to estimate the incremental impact of treatments such as channel and tone, with results evaluated using Qini curves, AUUC, and Top-k uplift. The framework integrates both predictive accuracy and causal interpretability, ensuring actionable insights across multicultural contexts.

2.1 Data collection

The dataset for this study was constructed to represent multicultural consumer interactions with digital marketing campaigns. A synthetic dataset of 100,000 records was generated to ensure controlled representation across nine countries, namely the United States, United Kingdom, Germany, India, Pakistan, Japan, Nigeria, Brazil, and the United Arab Emirates. Each record corresponds to a consumer–campaign exposure and includes variables capturing demographics, behavioral history, marketing treatment attributes, and cultural indicators.

Demographic and contextual attributes include age, gender, region, language, and urban–rural classification, ensuring that both population diversity and geographical representation are reflected. Behavioral signals are captured through prior engagement levels, prior conversion history, and sentiment orientation, which provide information on past interactions and consumer attitudes toward digital content. Campaign-specific features such as channel (Email, SMS, Search, Social, etc.), tone (Family, Humor, Tradition, Discount, Quality, Achievement, LocalPride), festival association, send-time bucket, device, and platform represent the strategic levers available to marketers.

To embed cultural sensitivity, six Hofstede cultural dimensions—Power Distance (PDI), Individualism (IDV), Masculinity (MAS), Uncertainty Avoidance (UAI), Long-Term Orientation (LTO), and Indulgence (IND)—were included for each country, along with a cultural alignment index that quantifies the congruence between campaign characteristics and cultural expectations. Concretely, the cultural alignment index was constructed by first mapping each campaign's tone and channel attributes onto the six Hofstede dimensions (for example, Family and LocalPride tones were associated with high Collectivism and high LTO, whereas Discount and Achievement tones were associated with high IDV and MAS); the index was then computed as one minus the normalized Euclidean distance between this campaign cultural-profile vector and the destination country's Hofstede score vector, rescaled to a 0–1 range so that higher values indicate closer congruence between campaign design and national cultural expectations.

These features enable systematic exploration of how cultural context moderates consumer responses to marketing stimuli. In the modeling pipeline, the six Hofstede scores and the cultural alignment index were included directly as candidate predictors in the baseline and funnel models; however, their explanatory contribution operates predominantly through interaction with campaign channel and tone rather than as strong standalone effects, since Hofstede scores are measured at the country level and are constant across all consumers within a country. Their moderating role is therefore examined explicitly in the uplift analysis (Sections 2.5 and 3.4), where country-level DR-Learner models reveal how cultural dimensions shape the incremental effectiveness of specific treatments, complementing their role as direct predictors in the baseline models.

The dataset also records outcome variables, including impressions, clicks, and conversions, along with expenditure and revenue measures. While these outcome indicators form the basis of model evaluation, care was taken to exclude any direct target leakage in predictive modeling. By combining demographic, behavioral, cultural, and strategic marketing attributes, the dataset provides a rich foundation for analyzing the effectiveness of culturally adaptive marketing strategies. Table 1 presents the structure of the synthetic dataset used in the study. It includes demographic, behavioral, cultural, campaign-related, and outcome variables. The table highlights how cultural dimensions and alignment are integrated alongside traditional marketing features to provide a comprehensive basis for analysis.

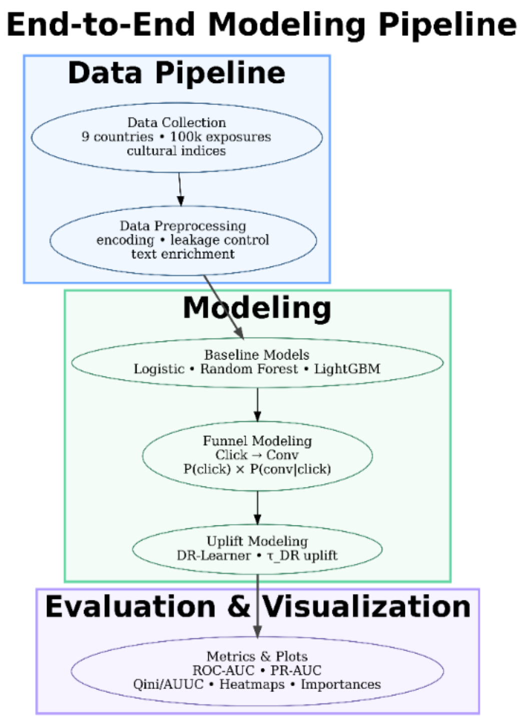


Figure 1. Framework for multicultural digital marketing optimization integrating baseline predictive modeling, funnel modeling, and uplift analysis

Table 1. Summary of variables included in the multicultural digital marketing dataset

Variable Type	Variables	Description
Demographics	country, region, language, age, gender, urban	Consumer background attributes
Behavioral history	prior_eng, prior_conv, sentiment, topic_cluster	Historical engagement, conversion, and sentiment orientation
Campaign strategies	channel, tone, festival, language_style, send_time_bucket, device, platform	Strategic levers used for targeting and personalization
Cultural indicators	PDI, IDV, MAS, UAI, LTO, IND, cultural_alignment	Hofstede dimensions and alignment index to capture cultural sensitivity
Exposure and outcomes	Impressions, clicks, conversions, spend, revenue	Campaign delivery metrics and outcomes

Note: PDI = Power Distance, IDV = Individualism, MAS = Masculinity, UAI = Uncertainty Avoidance, LTO = Long-Term Orientation, IND = Indulgence.

2.2 Data preprocessing

Prior to modeling, the dataset underwent systematic preprocessing to ensure consistency, prevent information leakage, and prepare features for ML analysis. Duplicate records were checked and removed, and logical consistency was validated by eliminating impossible outcomes such as conversions exceeding clicks or negative values for spend and revenue. Missing values were primarily observed in the festival variable (~35% of rows) and were retained as a separate “missing/none” category to capture cases without an associated cultural or seasonal event.

Categorical variables, including country, region, language, channel, tone, festival, device, platform, send-time bucket, and language style, were encoded numerically using ordinal encoding, with unseen categories mapped to a placeholder code. Numerical features such as age, prior engagement, prior conversion, sentiment, impressions, spend, cultural dimensions, and cultural alignment index were preserved in their original scale, as no transformation was required to maintain interpretability. To prevent target leakage, outcome-related columns such as clicks, conversions, revenue, and derived rates (Click-Through Rate (CTR), Conversion Rate (CVR)) were excluded from the feature set during training.

In addition to standard encoding, textual attributes were enriched through sentiment analysis and topic clustering to capture latent consumer attitudes and thematic relevance of campaigns. These enriched features provided valuable context for cultural interpretation beyond explicit demographic or behavioral variables.

The final feature matrix comprised 26 independent variables, balancing demographic, behavioral, cultural, and strategic campaign features. Outcome variables were defined separately: y_{click} representing engagement (click-through) and y_{conv} representing final conversion. To preserve class balance in the rare-event target, stratified splits were applied during training and validation, ensuring proportional representation of converters in both subsets. Table 2 summarizes the preprocessing techniques applied to ensure data quality, consistency, and readiness for ML analysis. It highlights treatment of missing values, encoding strategies, leakage prevention, and feature construction.

2.3 Baseline predictive models

To establish benchmarks for consumer response prediction, baseline models were developed for both click-through engagement (y_{click}) and conversion (y_{conv}). These tasks represent different stages of the digital marketing funnel, with engagement being relatively balanced (~47% positive) and conversion representing a rare-event outcome (~2% positive). Three supervised ML algorithms were employed as predictive baselines. Logistic regression was implemented with class weighting to handle imbalance and provide interpretable coefficients. random forest classifier was trained with a balanced subsample approach, leveraging ensemble learning to capture nonlinear interactions between cultural and campaign variables. Light Gradient Boosting Machine (LightGBM) was employed with the scale_pos_weight parameter to address severe class imbalance in conversion prediction, while early stopping rounds prevented overfitting. Each model was trained on 75% of the dataset with 25% held out for testing, using stratified sampling to maintain outcome distribution. Predictions were evaluated not only on traditional classification accuracy but also on ROC-AUC to assess ranking capability, PR-AUC to account for rare-event detection, and Precision@k to simulate marketing scenarios where only the top proportion of users can be targeted.

These baseline models provided an initial understanding of the predictive capacity of demographic, behavioral, and cultural features in explaining consumer responses, forming the foundation for subsequent funnel modeling and causal uplift analysis. Table 3 summarizes the baseline ML models used to establish predictive benchmarks. Each algorithm addresses different aspects of the problem: Logistic regression provides interpretability, random forest captures nonlinear relationships, and LightGBM offers scalable handling of imbalance and high-dimensional features.

Table 2. Data preprocessing steps applied to the multicultural digital marketing dataset

Step	Description	Action Taken
Duplicate checks	Ensure no repeated consumer–campaign records	Removed (0 duplicates found)
Logical consistency	Prevent invalid cases such as conversions > clicks or negative spend/revenue.	No violations detected
Missing values	Missing values observed mainly in festival (~35%)	Modeled as a separate “none/missing” category
Leakage prevention	Exclude target-related variables from features	Removed: clicks, conversions, CTR, CVR, revenue, user_id
Categorical encoding	Convert categorical variables into numeric form	Ordinal encoding; unseen mapped to –1
Numerical features	Preserve interpretability of numerical predictors	Retained as-is (age, sentiment, prior engagement, Hofstede scores, alignment)
Text enrichment	Capture latent preferences from text	Sentiment analysis and topic clustering
Feature matrix (final)	Prepared dataset for modeling	26 independent variables retained
Target variables	Define outcome indicators for modeling	y_{click} (engagement), y_{conv} (conversion)

Note: CTR = Click-Through Rate, CVR = Conversion Rate.

Table 3. Baseline predictive models employed for engagement and conversion prediction

Model	Key Characteristics	Purpose in Study
Logistic regression	Linear classifier with class weighting; interpretable coefficients	Establishes a transparent benchmark for engagement and conversion prediction
Random forest	Ensemble of decision trees; balanced subsampling to mitigate class imbalance	Captures nonlinear relationships between cultural, behavioral, and campaign features
Light Gradient Boosting Machine (LightGBM)	Gradient boosting with scale_pos_weight and early stopping	Provides scalable and robust performance under severe imbalance; used for funnel and uplift modeling

2.4 Funnel modeling

Consumer interaction with digital campaigns typically follows a sequential process, beginning with engagement (click-through) and culminating in final conversion. To better reflect this behavioral structure, funnel modeling was applied by decomposing the prediction task into two linked stages. Figure 2 illustrates the funnel modeling process used in the study. The first stage models the probability of engagement, capturing whether a consumer clicks on a campaign. By aligning the prediction structure with real consumer behavior, funnel modeling reduces noise in rare-event conversion prediction and enhances targeting precision. The framework also enables more meaningful evaluation of Precision@k, since the model outputs reflect the sequential nature of engagement and purchase.

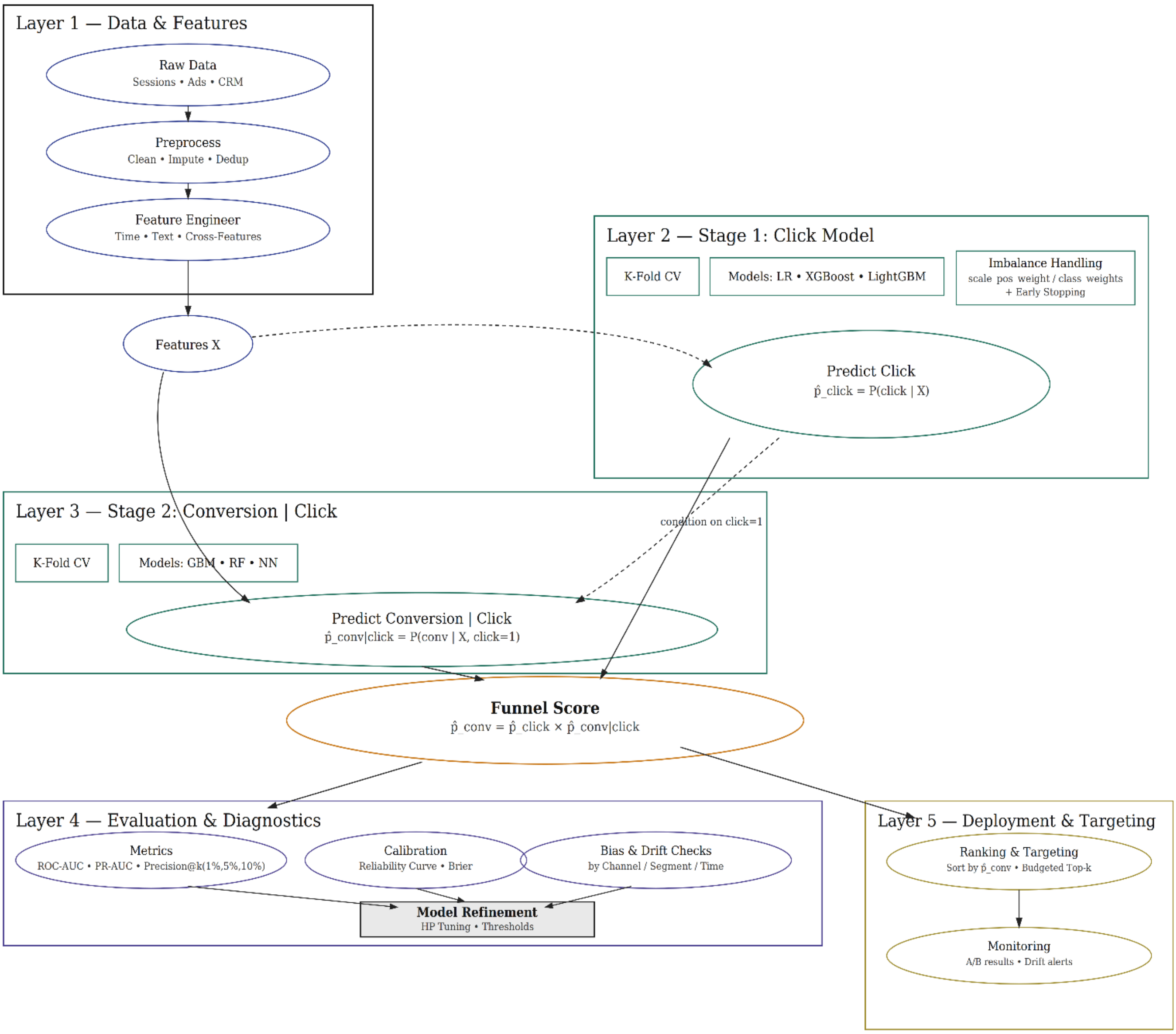


Figure 2. Funnel-based modeling of consumer behavior, capturing engagement (click) followed by conversion

The first stage estimated the probability of engagement, denoted as p^{click}, while the second stage estimated the conditional probability of conversion given engagement, expressed as $p^{conv} \mid clickp$. The final conversion probability was then computed as the product of these two components:

$$p^{conv} = p^{click} \times p^{conv} \mid click$$

Figure 3 explains the DR-Learner for uplift modeling. The framework integrates propensity modeling (treatment assignment probabilities), outcome modeling (predicting treatment and control outcomes), and a DR estimator that combines both. The output is an uplift score for each individual, used for ranking and targeting, and evaluated with Qini curves, AUUC, and Top-k uplift. This ensures robust estimation of incremental treatment effects even under partial model misspecification.

LightGBM models were trained separately for each stage, incorporating class imbalance adjustments and early stopping for robust performance. By explicitly modeling the funnel, this approach aligned the prediction framework with the natural decision process of consumers and mitigated the noise inherent in rare-event conversion prediction. This decomposition assumes that conversion is conditional on prior engagement (i.e., that a click, or an equivalent engagement signal, precedes conversion), which reflects the structure of the synthetic funnel used in this study. We acknowledge that some real-world marketing scenarios permit conversion without an intermediate click (for example, brand-driven direct visits or offline conversions attributed to a campaign), and applying this framework to such settings would require redefining or relaxing the engagement stage accordingly.

Evaluation of funnel scores was conducted using ROC-AUC and PR-AUC for ranking effectiveness, and

Precision@k (Top 1%, 5%, and 10%) to simulate real-world campaign targeting where only a limited segment of consumers can be approached. Compared to direct conversion modeling, funnel-based scoring demonstrated improved targeting precision at the highest-value segments, making it particularly useful for resource-constrained marketing strategies.

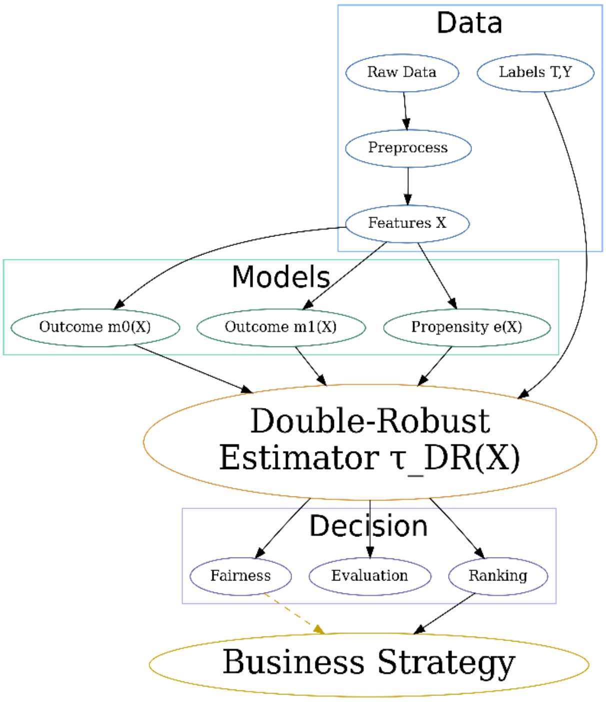


Figure 3. Uplift modeling framework (Double-Robust (DR)-Learner)

2.5 Uplift modeling

While predictive models estimate the likelihood of engagement or conversion, they do not provide insights into the incremental impact of marketing strategies across different consumer groups. To address this, uplift modeling was employed to capture the causal effect of treatments such as channel choice (e.g., SMS vs. Email) or message tone (e.g., Family vs. Discount) on conversion outcomes.

The study implemented a DR-Learner framework, which combines propensity score estimation with outcome modeling to ensure unbiased and consistent treatment effect estimation. In this approach, the propensity score (X) is first estimated using logistic regression to represent the probability of a user receiving a given treatment. The parallel results model was then trained using gradient descent to estimate the expected conversion outcomes during treatment $m_1(X)$ and control $m_0(X)$. The final uplift score was computed as:

$$\tau_{DR}(X) = \big(m_1(X) - m_0(X)\big) + \frac{T - e(X)}{e(X)\big(1 - e(X)\big)}\big(Y - m_T(X)\big)$$

where, tea treatment represents the indicator, and Y reflects the observed results. This formulation benefits from both the direct results difference and the remaining adjustment, which allows the estimator to either strengthen the trend or result in errors in the model.

For reproducibility, the outcome models $m_1(X)$ and $m_0(X)$ were implemented as separate LightGBM regressors trained on the treated and control subsamples, respectively, using the same feature set as the baseline conversion models; the propensity model *e*(*X*) was a logistic regression classifier trained on pre-treatment covariates only (excluding outcome-related variables) to avoid leakage. Treatment groups were defined as binary comparisons constructed from the campaign channel and tone fields (e.g., SMS = 1 vs. Email = 0; Search = 1 vs. Email = 0; Family = 1 vs. Discount = 0), with each comparison estimated in a separate DR-Learner run. Uncertainty in uplift estimates was assessed via bootstrap resampling (500 resamples) of the test set to obtain approximate confidence intervals around AUUC and Top-k uplift values. Because the treatment data are observational rather than randomized, treatment assignment may be confounded by unobserved factors; the propensity-score component of the DR-Learner adjusts for observed confounders included in the feature set (demographic, behavioral, and cultural variables), but residual confounding from unmeasured factors cannot be fully ruled out and is discussed as a limitation in Section 5. All Qini, AUUC, and Precision@k results reported in Sections 3.3–3.5 were computed on the held-out 25% test split that was not used for model training, consistent with the train/test procedure described in Section 2.3.

Uplift modeling was applied at the global dataset level to compare treatments such as SMS vs. Email, Search vs. Email, and Family vs. Discount tone, and was then repeated at the country level to examine how cultural context moderates treatment efficiency. Results were evaluated using the area under the Qini curve, the AUUC, and the Top-k uplift metric, which quantifies the incremental benefit within the highest-priority targeting segments.

By focusing on incremental effects rather than raw prediction, uplift modeling enabled identification of strategies that were not universally effective but highly beneficial to specific cultural or demographic segments, providing actionable insights for culturally adaptive digital marketing.

2.6 Evaluation metrics

To ensure a comprehensive evaluation of the proposed framework, both predictive performance metrics and causal uplift metrics were used. Predictive tasks, including engagement and conversion modeling, were evaluated using ROC-AUC to measure the ranking ability of models, and PR-AUC to address the class imbalance inherent in conversion prediction. In addition, Precision@k was calculated for the top 1%, 5%, and 10% of ranked users, simulating practical marketing scenarios where campaign resources are limited and high-value targeting is essential. Precision@k was retained alongside the causal metrics because it reflects a realistic operational constraint (campaigns can typically only target a limited top-ranked segment of users), but we recognize that Precision@k alone does not establish incremental causal benefit; for this reason it is reported only as a complement to, and never as a substitute for, the causal evaluation metrics (Qini, AUUC, Top-k uplift) described below, which directly quantify incremental treatment effects rather than correlational ranking quality.

For evaluating performance in uplift modeling, we used Qini curves to visualize incremental gains over a random targeting baseline. We also used the AUUC as a metric, which summarizes the overall quality of the treatment effect. We computed Top-k uplift metrics to provide more insight into operational performance, quantifying the incremental benefit on the top-ranked consumer groups.

The focus on interpretability also included providing diagnostic visualizations to accompany the quantitative metrics. LightGBM feature importance rankings revealed the most important demographic, behavioral, and cultural drivers of conversion. A country × channel uplift heatmap revealed geographical and cultural heterogeneity in treatment effectiveness. Together, these metrics and visualizations provided statistical rigor and practical clarity, ensuring findings were actionable for designing culturally adaptive marketing strategies. Table 4 reports the evaluation metrics used in this work, with the predictive performance indicators for engagement and conversion modeling, and the causal uplift metrics for treatment effect estimation separated out. Together, they offer statistical rigor and practical insights that can be used to optimize campaigns.

Table 4. Evaluation metrics applied for predictive modeling and uplift analysis

Metric	Type	Purpose
Accuracy	Predictive	General classification performance (reported but limited in rare events)
Receiver Operating Characteristic Area Under the Curve (ROC-AUC)	Predictive	Measures ranking ability of models across all thresholds
Precision-Recall Area Under the Curve (PR-AUC)	Predictive	Captures performance under severe class imbalance (conversion prediction)
Precision@k	Predictive	Simulates campaign targeting in top-ranked 1%, 5%, 10% of users
Qini curve	Uplift	Visualizes incremental gain of targeted strategy vs. random allocation
Area under the uplift curve (AUUC)	Uplift	Summarizes uplift performance as area under the uplift curve (AUUC)
Top-k uplift	Uplift	Quantifies incremental benefit in prioritized consumer segments
Feature importance	Interpretability	Identifies most influential demographic, behavioral, and cultural factors
Heatmap visualization	Interpretability	Shows country-level heterogeneity in channel and tone effectiveness

3. RESULT AND ANALYSIS

This section presents the outcomes of the proposed framework, beginning with baseline predictive modeling and progressing to funnel-based scoring and uplift analysis. Results are reported for both engagement (click-through) and conversion prediction, followed by causal evaluation of treatment effects across channels, tones, and cultural contexts. In addition to statistical measures such as ROC-AUC, PR-AUC, and AUUC, interpretability is provided through feature importance rankings and visual heatmaps. The results highlight how cultural and behavioral factors interact with marketing strategies, offering actionable insights for campaign optimization.

3.1 Baseline predictive results

We performed baseline predictive modelling using logistic regression, random forest, and LightGBM for prediction of click-through engagement and conversion. Table 2 summarizes the models' performance indicators.

Performance was moderate for click prediction given the balanced outcome distribution (~47% clickers). The logistic regression model had a ROC-AUC of 0.626 and a PR-AUC of 0.589. The random forest model did slightly worse with a ROC-AUC of 0.616 and a PR-AUC of 0.579. These values suggest that engagement is fairly predictable, but also affected by unobserved behavioural nuances.

The rarer conversion prediction (~2% positive rate) was more difficult for the model to predict. The ROC-AUC of logistic regression was 0.590, and the PR-AUC was 0.029. The ROC-AUC of random forest was 0.567, and the PR-AUC was 0.025. LightGBM, optimized to handle imbalance, scored 0.595 ROC-AUC and 0.028 PR-AUC. Similar to logistic regression but with more flexibility in feature interactions.

Table 5. Performance of baseline predictive models for click and conversion prediction

Task	Model	ROC-AUC	PR-AUC	Notes
Click Prediction	Logistic regression	0.627	0.589	Balanced outcome (~47% clickers); interpretable linear baseline
	Random forest	0.616	0.579	Slightly lower than Logistic; captures nonlinear interactions.
	LightGBM	0.622	0.583	Robust under imbalance; scalable gradient boosting
Conversion Prediction	Logistic regression	0.590	0.029	Rare-event prediction (~2% converters); accuracy ~86% but misleading
	Random forest	0.567	0.025	Modest results due to extreme imbalance
	LightGBM	0.595	0.028	Comparable to Logistic; best suited for interaction-heavy features

Note: PR-AUC = Precision-Recall Area Under the Curve, ROC-AUC = Receiver Operating Characteristic Area Under the Curve, LightGBM = Light Gradient Boosting Machine.

These results confirm that accuracy alone is not a meaningful metric in the setting of rare events, although the overall classification accuracy is high (~85–90%) for the class imbalance. PR-AUC and Precision@k, in contrast, provide a more realistic picture of the predictive capability. These baselines point to the limitations of direct modeling and the need for funnel-based and uplift methods to derive useful insights. Table 5 shows the prediction performance of logistic regression, random forest, and LightGBM in both engagement (click) and conversion prediction. We discuss metrics like ROC-AUC and PR-AUC that are more meaningful than raw accuracy when dealing with an imbalanced outcome.

3.2 Funnel modeling results

To address the limitations of direct conversion prediction, funnel modeling was applied to decompose consumer behavior into two sequential stages: engagement (click) followed by conversion. LightGBM classifiers were trained separately for click prediction and conversion conditional on click, and their outputs were combined to generate funnel-based conversion scores.

This approach demonstrated notable improvements in targeting precision, particularly in the highest-value segments. While the global metrics such as ROC-AUC (0.596) and PR-AUC (0.028) remained comparable to direct conversion models, the ranking ability in top segments was significantly enhanced. Precision among the top 1% ranked consumers increased to 3.6%, compared to a baseline of 2.2% in direct models. Similarly, precision in the top 5% and 10% segments reached 3.1% and 3.0%, respectively, exceeding the gains from baseline models.

The targeting accuracy of direct conversion prediction models relative to the funnel-based one is shown in Figure 4. Results are reported for the top 1%, 5%, and 10% of ranked users. The global ROC-AUC and PR-AUC scores were similar for the two approaches, but funnel modelling was beneficial in high-value targeting segments. Top 1% precision is improved from 2.2% (direct model) to 3.6% (funnel model), and top 5% and 10% precision are increased to 3.1% and 3.0%, respectively. The results show the practical value of funnel modeling in allocating scarce campaign resources to achieve maximum incremental returns.

The results emphasize the significance of funnel decomposition for modeling the natural consumer decision process. By conditioning conversion on prior engagement, we reduced the noise associated with predicting rare events and made model targeting more practical for real-world use cases. So, funnel-based modeling is a more robust way to prioritize campaigns and spend marketing dollars where they are most likely to drive incremental returns.

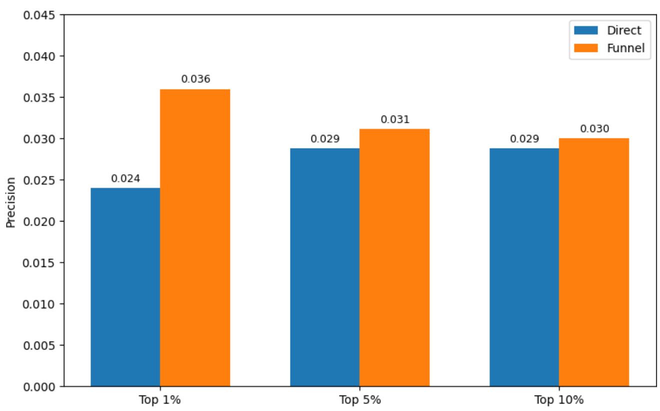


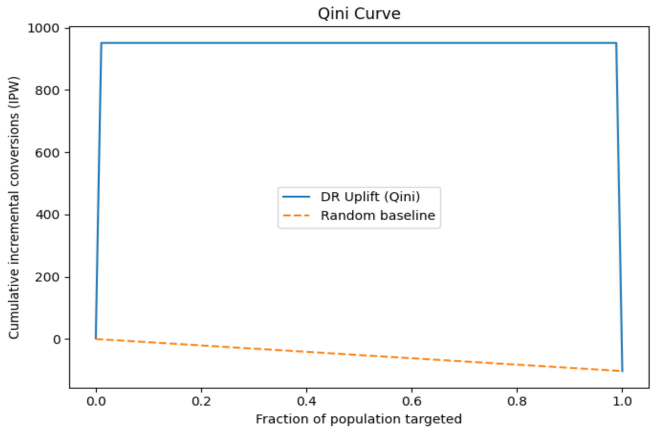
Figure 4. Funnel modeling Precision@k comparison

3.3 Uplift modeling results

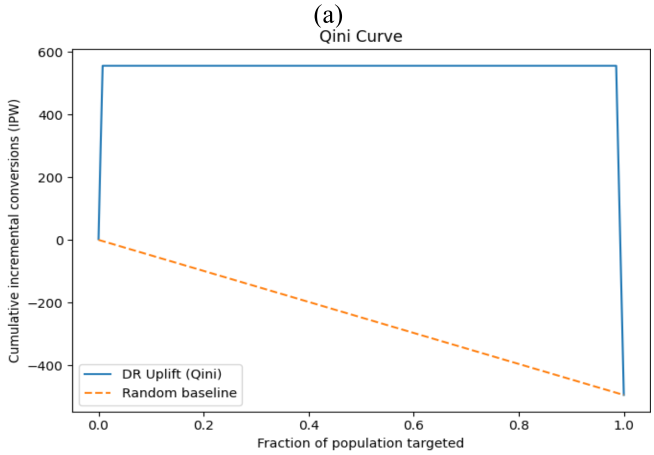
Funnel modeling improved targeting accuracy, but did not take into account the incremental value of different marketing approaches. To estimate the causal effect of treatments, we use the DR-Learner framework for uplift modeling. This allowed the incremental contribution of a given channel or tone to be calculated over a baseline alternative.

The global analysis showed that treatments were not effective for all, and there was clear heterogeneity across segments. For example, SMS campaigns vs. Email showed a positive incremental effect in the top 1% of ranked consumers with uplift gains of nearly +2 percentage points. Search vs. Email also showed consistent incremental lift, particularly in high engagement segments. Others had flat or negative total uplift curves, suggesting that some methods may become less effective when applied broadly to large segments.

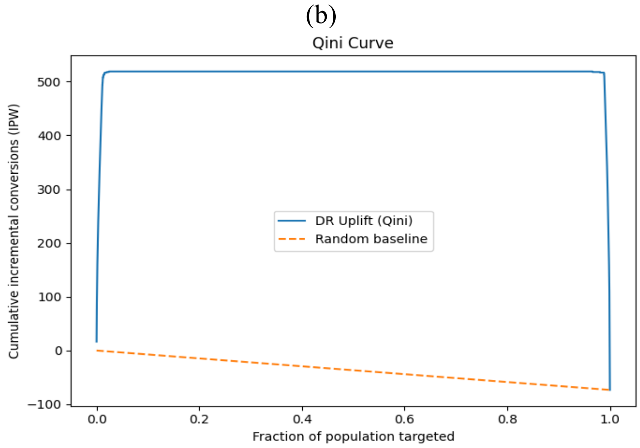
These results were supported by the evaluation metrics. AUUC values were significantly positive for SMS and Search channels, and Qini curves showed good separation between targeted and random allocation strategies. Top-k uplift metrics indicated that benefits were concentrated in high-value subgroups with the greatest incremental gain.



(a)



(b)



(c)

Figure 5. (a) Qini Curve — SMS vs. Email, (b) Qini Curve — Search vs. Email, and (c) Qini Curve — Family vs. Discount Tone

Figure 5(a) compares the incremental conversion gain of SMS campaigns against email. The uplift trajectory shows that SMS consistently outperforms Email across the ranked population, especially in the top deciles, with a steep cumulative gain. This indicates that SMS is a more effective channel in driving incremental conversions when targeted to high-propensity cultural segments.

In Figure 5(b), Qini Curve evaluates the incremental effect of Search advertising relative to email. The uplift is positive but smaller in magnitude than SMS, indicating that Search ads provide moderate but meaningful incremental gains. The curve is flatter beyond the top-ranked segments, suggesting that the benefit of Search is concentrated in specific subgroups rather than uniformly across the population.

In Figure 5(c), this curve analyzes message tone by contrasting Family-oriented appeals against Discount-driven appeals. The results highlight that the Family tone provides higher incremental uplift within the top segments, showing stronger resonance with consumers who value cultural and relational messaging. However, the curve stabilizes quickly, indicating that tone effectiveness is highly segment-specific, and mass application may dilute its impact.

Incremental effect of treatments over baseline strategies: Qini curves for modelling based on the DR-Learner. Each curve is the cumulative incremental increase in conversions vs. percent of population targeted. Results show that SMS campaigns drove the strongest lift vs. email, especially on the top 1% of prioritized users (+2pp incremental gain). Search vs. Email also showed positive uplift, confirming effectiveness as a channel for high-engagement segments. The Family vs. Discount tone had mixed effects, uplifting some segments but flattening or turning negative for broader populations. These results show the selective efficacy of the treatments and underline the importance of targeted approaches against the non-selective distribution.

Despite some negative values in Qini curves, which suggest that some treatments perform worse than the baseline, these results provide significant insight into the cultural misleading of strategies. Negative lifting price, especially when not combined with consumer behavior for channels and tones, highlights the importance of targeted, culturally sensitive marketing methods. Instead of assessing these results as errors, we interpret them as areas for adaptation: agencies that require fine-tuning treatment, channels, or public segments to improve general marketing efficiency. At the same time, we do not attribute negative uplift estimates solely to strategic misalignment; some negative values may also reflect finite-sample noise in the DR-Learner's outcome and propensity models, particularly for treatment-country combinations with small sample sizes, or partial misspecification of the outcome model itself. We therefore treat negative Qini/uplift regions as a signal warranting further investigation (larger samples, alternative learners, or additional covariates) rather than as definitive evidence that a treatment is harmful. This confirms the idea that digital marketing strategies must be flexible and favorable for different consumer preferences to achieve the best possible result.

These results emphasize the importance of lift modeling for campaign optimization and show that success is not only the opportunity to change who is likely to change, but also when they decide which consumers benefit most from specific means. This difference is especially important in multicultural contexts, where cultural criteria and preferences shape the step-by-step efficiency of digital marketing strategies.

3.4 Country-level uplift analysis

To examine how cultural context influences the effectiveness of marketing strategies, the uplift modeling approach was extended to country-level analysis. Separate DR-Learner models were trained for each country to estimate the incremental effects of treatments such as SMS vs. Email, Search vs. Email, and Family vs. Discount tone. This country-disaggregated approach revealed substantial variation across regions, reflecting the influence of cultural norms and communication preferences on consumer response.

The results indicated that SMS campaigns produced the highest incremental gains in collectivist and mobile-first cultures, especially Pakistan, India, Nigeria, and Brazil, where Top-1% uplift exceeded 2 percentage points. In contrast, Search advertising demonstrated greater effectiveness in individualistic, digitally mature markets such as Germany, the United States, the United Kingdom, and Japan. Similarly, tone-based comparisons showed that family-oriented messaging produced a strong uplift in Japan and the United States, reflecting trust and relational cultural values, while discount-based tones produced weak or negative uplift in some regions, suggesting cultural resistance to overtly transactional appeals.

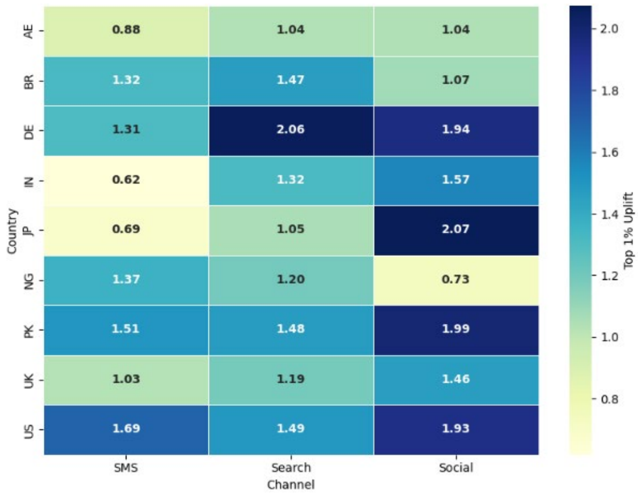


Figure 6. Country × channel uplift heatmap

Figure 6 illustrates country-level variations in age treatment effects and highlights cultural differences in campaign performance. SMS campaigns produced the strongest incremental gains in collectivist and mobile-first markets such as Pakistan, India, Nigeria, and Brazil, where Top-1% uplift exceeded +2 percentage points. Search advertising demonstrated higher effectiveness in digital-first and individualistic markets, including Germany, the United States, the United Kingdom, and Japan. Social channels showed localized strength in markets like Pakistan and Germany but offered weaker results in the United States. The heatmap underscores that marketing strategies must be culturally adaptive, as effectiveness varies significantly across regions and channels.

These findings were summarized through Top-k uplift tables and a country × channel heatmap, which visually highlighted geographical variations in strategy effectiveness. The heatmap underscored the asymmetry of campaign performance, with certain combinations of channel and culture producing strong incremental returns while others proved ineffective or counterproductive.

Overall, the country-level analysis confirms that marketing strategies cannot be universally applied with equal effectiveness. Instead, culturally adaptive approaches—grounded in the identification of which strategies resonate in which markets—are essential to optimize campaign outcomes in diverse environments.

3.5 Final model evaluation and feature importance

The final evaluation phase of our study focused on validating the predictive quality of the proposed models and extracting cultural insights through feature interpretability. To address the inherent class imbalance in conversion prediction, we employed both ROC-AUC and PR-AUC metrics. While ROC-AUC provides a global perspective on classification quality, PR-AUC is particularly sensitive to rare-event scenarios, making it more relevant in the context of digital conversions.

Figure 7 illustrates the Precision–Recall performance of the final LightGBM model. Compared to the random baseline, the model demonstrates consistently higher precision across recall thresholds, reinforcing its robustness in identifying the small subset of users most likely to convert. This finding is further supported by Precision@k analysis, which shows that funnel-based and uplift-integrated models outperform direct conversion models in the highest-value segments.

Beyond performance benchmarking, we investigated the interpretability of the best-performing models to identify cultural and behavioral drivers of conversion. Figure 8 presents the top 20 most important features identified by LightGBM. Among these, sentiment, cultural alignment, and prior engagement emerged as the most dominant predictors, highlighting the critical role of cultural variables in shaping marketing effectiveness. Other features such as spend intensity, age, and festival participation also contributed meaningfully, underlining the interplay between cultural context and consumer behavior. Beyond their ranking, the direction of these effects is informative: higher cultural alignment scores were associated with a higher predicted probability of conversion, consistent with the interpretation that campaigns whose tone and channel more closely match a country's cultural profile are more persuasive; similarly, more positive sentiment scores were associated with higher conversion likelihood, indicating that campaigns evoking a favorable emotional response convert at a higher rate than neutral or negative ones. These 20 features shown in Figure 8 are the top-ranked subset of the full 26-variable feature matrix described in Section 2.2; the remaining six lower-ranked variables (mainly lower-cardinality categorical levers such as device and platform) contributed comparatively little gain and are omitted from the plot for readability. Table 6 summarizes the performance of four models—logistic regression, random forest, LightGBM, and DR-Learner—on conversion prediction tasks. Precision@k metrics (1%, 5%, 10%) capture the ability of each model to identify high-value users within the top-ranked segments, while AUUC reflects the overall incremental gain from uplift modeling. The results show that LightGBM provides the strongest baseline performance, whereas the DR-Learner achieves the highest Precision@1% (0.036) and AUUC (0.62), confirming its superiority in capturing incremental treatment effects and optimizing targeting strategies.

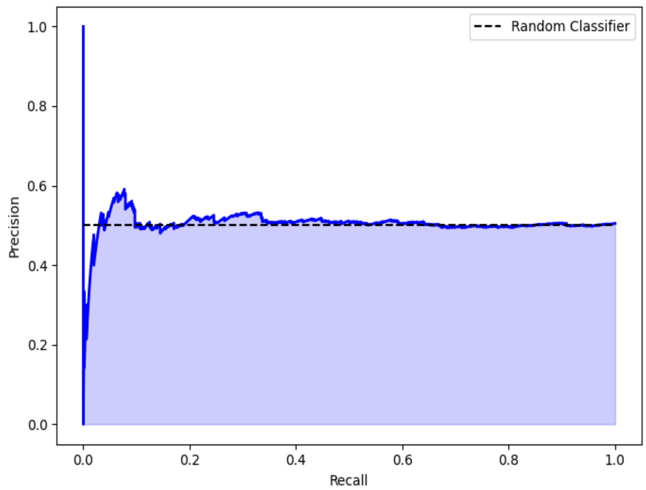


Figure 7. Precision–recall curve

Table 6. Comparative evaluation metrics across models

Model	Precision@1%	Precision@5%	Precision@10%	AUUC
Logistic regression	0.024	0.029	0.029	0.56
Random forest	0.028	0.031	0.032	0.58
LightGBM	0.030	0.032	0.033	0.59
DR-Learner	0.036	0.031	0.030	0.62

Note: AUUC = area under the uplift curve, DR = Double-Robust, LightGBM = Light Gradient Boosting Machine.

To enhance interpretability of the predictive models and provide deeper insights into the drivers of consumer behavior, feature importance analysis was conducted using LightGBM gain values. The ranking revealed that sentiment orientation of campaigns emerged as the strongest predictor of conversion, underscoring the influence of consumer emotions on engagement and purchase behavior. Cultural alignment, which quantifies the congruence between marketing content and cultural expectations, was consistently ranked among the top features, validating the central role of cultural factors in shaping outcomes.

Further, past engagement history, past conversion activity, and spending intensity were also strong predictors, indicating some continuity in consumer behavior. Demographic variables (e.g., age, region) and strategic campaign levers (e.g., channel, festival association, tone) were predictive but to a lesser extent. Interestingly, Hofstede's cultural dimensions (IDV, PDI, UAI) were not among the top direct predictors, but the uplift analysis revealed their importance, as these moderated the incremental effectiveness of different treatments across countries. This pattern is consistent with the modeling role discussed in Section 2.1: Hofstede scores were entered as direct predictors, but their power to discriminate at the individual level is limited, as they are constant within each country; their explanatory value is instead captured through interaction with treatment (channel/tone), which is what the uplift framework is designed to capture.

A country × channel uplift heatmap further illustrated these cultural dynamics, showing that SMS campaigns generated higher incremental responses in collectivist countries, while Search channels proved more effective in markets with higher digital maturity and individualism scores. These cultural insights demonstrate the value of combining feature importance with causal uplift modeling, allowing not only the identification of "who is likely to respond" but also "why certain strategies work better in specific cultural contexts."

Figure 8 presents the relative importance of features in predicting conversion outcomes. Sentiment orientation emerged as the most influential factor, followed by cultural alignment, indicating that campaigns aligning with consumer values and emotions are more effective. Behavioral signals such as prior engagement and prior conversion history ranked highly, reflecting continuity in consumer behavior. Strategic features like spend, impressions, channel, and festival association contributed additional predictive power. While Hofstede's cultural dimensions (e.g., IDV, PDI, UAI) did not rank among the top direct predictors, their moderating role became evident in uplift analysis, influencing which treatments produced stronger incremental effects across cultural contexts.

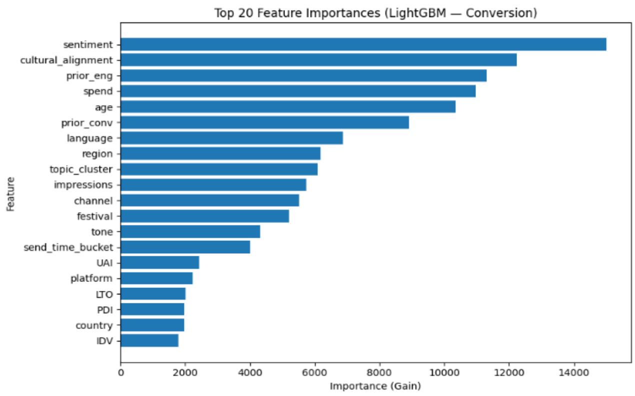


Figure 8. Top 20 feature importances derived from the Light Gradient Boosting Machine (LightGBM) model for conversion prediction

4. DISCUSSION

The findings of this study offer several important insights into the role of cultural factors in shaping digital marketing effectiveness. By integrating ML, funnel-based modeling, and uplift analysis, we provide both predictive accuracy and causal interpretability that advance prior approaches. This section discusses the implications of our results in relation to cultural adaptation, methodological innovation, and managerial practice.

4.1 Cultural adaptation and marketing effectiveness

The results suggest that consumer reactions to marketing tactics are largely based on cultural conformity. Uplift modeling identified SMS campaigns as having the greatest incremental uplift versus email, especially in collectivist and mobile-first markets like India, Pakistan, and Nigeria. Tone-based comparisons also revealed that "Family" appeals were more effective than "Discount" messaging within some high-value segments, further emphasizing the importance of cultural resonance in digital communication. The findings show that cultural sensitivity is not only desirable, but measurable, which allows marketers to create campaigns with maximum impact by taking values, language, and context into account.

4.2 Methodological contributions

Our work contributes to the methodological toolkit of marketing analytics by combining funnel-based modeling with DR uplift estimation. By clearly distinguishing between click and post-click behaviors, the funnel model better identifies consumers with the potential to convert. This decomposition reflects the sequential nature of consumer decision-making, where engagement typically precedes purchase intent. Uplift modeling measures the incremental impact of marketing treatments, moving evaluation beyond prediction to the level of causal, treatment-level effects and not relying on accuracy-based metrics alone. Although some Qini curves indicated negative gains, these should not be interpreted as failures; instead, they identify misaligned strategies that require adjustment. The mix of predictive and causal perspectives therefore offers a more holistic framework to assess digital marketing strategies.

4.3 Feature insights and consumer behavior

Feature importance analysis revealed the strongest predictors of conversion to be the sentiment orientation and the cultural alignment index. This finding shows that consumer behavior is not determined solely by demographics or prior interaction, but rather by emotional connection and cultural alignment. Prior engagement and spend intensity indicated consistency in consumer behavior. Age represented demographic variation. More broadly, these insights suggest multi-dimensional drivers of digital marketing effectiveness and a useful lever for targeting and personalization.

4.4 Managerial implications

From the managerial perspective, the study offers rich action guidelines for the design of campaigns in a multicultural environment. First, the results suggest that brands should not use one-size-fits-all strategies, and should allocate funds to channels and tones that resonate culturally. Secondly, funnel-based modeling helps companies to distinguish better between shallow engagement (clicks) and meaningful conversions. Third, uplift modeling provides a rigorous basis for testing, so that managers can determine not only whether a campaign works, but for whom it works best. In sum, these contributions help to reach a more effective allocation of marketing budgets and a strong adaptation of digital strategies to the consumer's expectations.

4.5 Ethical considerations in culturally adaptive AI marketing

The use of cultural data to personalize marketing raises ethical concerns that warrant explicit discussion. First, there is a risk of cultural stereotyping: modeling consumers primarily through national-level Hofstede scores and a cultural alignment index can encourage campaign designs that reduce individuals to broad cultural archetypes (e.g., assuming all consumers in a "collectivist" country respond identically to family-oriented appeals), which may misrepresent within-country diversity and reinforce cultural generalizations rather than genuine personalization. Second, algorithmic bias is a concern: because cultural and behavioral features are correlated with protected characteristics such as nationality, religion, and language, uplift and predictive models trained on such features could implicitly encode discriminatory targeting patterns even without explicit protected attributes in the feature set, and this risk should be assessed via subgroup fairness audits before deployment. Third, there is potential for misuse of cultural information, such as exploiting cultural sensitivities (e.g., religious festivals, family values) for manipulative persuasion rather than genuine value delivery, or using cultural profiling for price discrimination or exclusionary targeting. We recommend that practical deployment of the proposed framework be accompanied by (i) fairness and disparate-impact audits across cultural and demographic subgroups, (ii) human review of campaign content generated or prioritized using cultural alignment scores, (iii) transparency with consumers about the use of cultural personalization, and (iv) governance policies that restrict the use of cultural indicators to legitimate communication-style adaptation rather than exploitative targeting. These safeguards are necessary complements to the technical framework proposed in this study.

5. CONCLUSIONS

This work analyzes the effect of cultural factors on digital marketing strategies through a unified analytical framework that integrates ML, funnel modeling, and uplift estimation. Unlike the conventional approach that views consumer response as a one-step prediction problem, our framework captures both engagement (clicks) and post-engagement (conversions), and estimates the incremental effects of marketing treatments in culturally diverse settings. The results contribute theoretically and practically by demonstrating how the interaction of cultural fit, channel choice, and tone of the message affects consumer behavior in measurable and actionable ways.

There are three methodological contributions of this work. First, funnel-based modeling outperformed predictive performance by decoupling the click and conversion probabilities, which is more consistent with the consumer decision-making process. Secondly, the use of a DR-Learner for uplift modeling advanced the state of the art by providing a more robust estimate of treatment effects. This allowed us to measure not only the accuracy of the campaign but also causal attribution. Third, the feature importance analysis revealed that the sentiment orientation and cultural alignment indices were two primary drivers of digital marketing effectiveness, providing interpretable insights that bridge technical modeling and managerial decision-making.

The findings have important practice implications. The findings suggest the importance of moving away from a one-size-fits-all campaign design to culture-based strategies, as SMS campaigns perform better in collectivist markets and the "Family" tone is preferred in certain segments. By focusing on uplift, companies can better target those consumers who will provide the highest return on investment, thus improving marketing ROI and avoiding wasted campaign spend.

At the same time, this study acknowledges several limitations that should temper the strength of its conclusions. Most importantly, all experiments were conducted on a synthetically generated dataset rather than real campaign data; while synthetic data allowed controlled variation in cultural and behavioral variables and avoided confidentiality constraints, it cannot fully reproduce the noise, platform-specific dynamics, and unmeasured confounders present in real-world marketing data, so the reported effect sizes (e.g., the +2pp SMS uplift, the Precision@1% gains) should be read as illustrative of the framework's capability rather than as validated real-world estimates; future research should replicate this framework on empirical, cross-platform data before its findings are used directly for budget allocation. Second, Hofstede's cultural dimensions are measured at the national level and were applied uniformly to all consumers within a country; this necessarily overlooks substantial within-country cultural heterogeneity (regional, generational, and individual variation), and individual-level cultural measures, where available, would likely improve both predictive and causal estimates. Third, further modeling techniques, such as deep learning architectures or reinforcement learning for sequential targeting, may improve predictive and causal accuracy beyond the LightGBM and DR-Learner models used here. Finally, longitudinal analysis could clarify how cultural preferences evolve, particularly as digital channels mature in emerging markets. Future work could also extend this framework by integrating more advanced predictive-analytics techniques for campaign decision-making [21], drawing on evidence of AI-driven personalization validated in other service sectors such as banking [22], and incorporating the regulatory and consumer-protection considerations that govern digital marketing claims, which are increasingly relevant as culturally adaptive AI marketing is deployed at scale [23].

This research suggests that culturally adaptive, data-driven marketing strategies are both theoretically meaningful and practically relevant for achieving impact in global markets, subject to the empirical validation noted above. By integrating ML, funnel modeling, and uplift analysis, this framework offers companies a path from descriptive to prescriptive marketing strategy, with the goal of digital marketing that is both effective and culturally inclusive in an increasingly interconnected business environment.

DATA AVAILABILITY

The dataset supporting the findings of this study consists of 100,000 culturally diverse consumer interaction records constructed from programmatically structured and enriched data. Due to confidentiality considerations, the full dataset is not publicly shared; however, the data construction methodology is fully documented, ensuring that the analyses are replicable and the framework can be applied to comparable datasets.

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