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DATA-DRIVEN PROMOTION STRATEGIES FOR FOLK ARTISTS

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ABSTRACT

The folk artists are very important in the process of conserving the intangible cultural heritage, however, their presence and access to the market are restricted by the disjointed promotional channels, informal marketing and lack of data-driven decisions. As the digital platforms and social media, as well as online marketplaces, continue to grow, there is an expanding possibility to use data analytics to advance reach, sustainability, and economic resilience of the folk art communities. This research aims, first of all, to design and test the data-driven promotion strategies and maximize the audience, engagement, and sales outcomes of folk artists without interfering with the culture. The research is based on a mixed-method, data-driven approach, which is an integration of descriptive analytics, prediction models based on machine learning, and audience segmentation methods. Materials of digital interactions obtained in the social media platforms, online exhibitions and e-commerce portals are processed with the help of feature extraction, clustering and supervised learning models to determine the major visibility and demand drivers. Random Forest and Gradient Boosting models are used to predict the probability of engagement and conversion, and the effectiveness of promotional strategy is tested with the help of A/B testing. The results of these experiments show that data-intensive promotion strategies enhance the audience engagement rate by 28-35 percent and sales conversion rate by 22-27 percent in comparison with conventional and intuition-based promotion. The values of precision and recall (greater than 0.85) in engagement prediction suggest that the model performs well. The results indicate the importance of individual content timing, platform-specific approach, and demographic targeting. Altogether, the given framework offers a scalable, evidence-based framework of empowering folk artists, making an informed promotional decision, and facilitating the long-term sharing of cultural heritage in digital ecosystems.

Keywords: Folk Artists, Data-Driven Promotion, Cultural Heritage Marketing, Audience Analytics, Digital Engagement Optimization

1. INTRODUCTION

Historically, the popularization of folk artists and traditional art forms has been based on localized events, social networks, government-sponsored fairs, and marketplaces by the middlemen. Although these methods have helped preserve the culture, they are becoming less sufficient in an economy that is digitally mediated and is marked by the visibility of platforms, algorithmic recommendation engines, and data-heavy models of engaging the audience Kasemsarn and Nickpour (2025), Lin et al. (2024). The folk artists tend to work in informal environments with minimal exposure to marketing, analytics tools and digital infrastructure which makes them low in discoverability, unstable revenue, and prone to market variances Wongpracha et al. (2024). Meanwhile, the digital platforms of the world community allow creating large amounts of data views of interaction, likes, shares, click-through, and purchases that are virtually untapped in terms of strategic decision-making in the folk art industry Ciuculescu and Luca (2024). This disconnection reveals a very serious technical and structural discontinuity between cultural production and data-driven promotion.

Technologically, traditional means of promotion are mostly intuition-based and unchanging and have no alternatives of feedback, optimization, and scalability. They fail to study the behavior of the audience, content performance and platform dynamics in a systematic manner and it is hard to find what kind of artwork appeals to which section of the audience, at which time and on which digital channel Kasemsarn (2024). Contrarily, the success of data-based marketing approaches in the related creative markets like music streaming, digital design and independent filmmaking has proven that analytics and machine learning are effective at improving visibility, engagement, and monetization Rodríguez et al (2021). Such methods have not, however, been adequately adjusted to the special requirements of the folk art, in which cultural fidelity, storytelling, and moral signification are equally significant, with regard to the business results Wang et al. (2021).

This gap is the main focus of this research as it aims at filling that gap by suggesting a technically-based, data-driven promotion framework that suits folk artists. The purpose of the study is to use data analytics and the machine learning models to facilitate evidence-based promotional choices without compromising on the cultural integrity. In particular, the study is aimed at defining the most critical drivers of digital engagement, the process of audience response modeling, and the promotion strategy refinement based on forecast and comparison Rubio-Hurtado et al. (2022). The proposed solution contrasts with generic digital marketing solutions, and the interpretable models and feature insights proposed can allow artists, cooperatives, and cultural institutions to interpret why a particular strategy is more successful and do not consider algorithms as black boxes Ramadhani and Indradjati (2023). Technically in terms of contribution, this paper places the problem of folk art promotion as a data science problem with heterogeneous data sources, feature engineering, predictive model, and performance evaluation. The study facilitates the structured pipeline through the introduction of promotion as a quantifiable process and is optimizable, making it simple to combine data collection, preprocessing, algorithms used in learning, and evaluation metrics in a single architecture Nursanty et al. (2023). On whole, the introduction sets the requirements of a data-driven, technically sound method of folk artists promotion, providing the basis of further passages which describe the computational frameworks, experimental validation and practical implications of the presented framework.

2. RELATED WORK AND TECHNICAL BACKGROUND

The study of digital marketing analytics in creative sectors has grown tremendously as more and more platform-based economies and data-filled interaction spaces have increased. Research in other industries, including music streaming, independent film-making, online crafts and digital design has shown that the usage of data about the audience behavior based on impressions, click-through rates, dwell time and purchase histories can be analyzed in a systematic manner to provide an optimized approach to promotional strategies Kasemsarn and Nickpour (2025), Lin et al. (2024). The methods of analytics-based methods typically utilize descriptive and diagnostic methods of measuring the performance of content in all the platforms, after which there are predictive models that help to predict results of engagement and revenue Wongpracha et al. (2024). These techniques have empowered dynamic pricing, personalized suggestions, and optimization of campaigns in the creative industries, which emphasizes the potential of data-sensitive promotion to substitute the method of decision-making based on humbleness. The majority of current frameworks however are structured around digitally native creators and platform integrated companies, with the assumption that data is always available and that content is in a standardized format Ciuculescu and Luca (2024).

There is previous research on the application of clustering algorithms to audience segmentation, the use of supervised learned models to predict engagement and demand and recommender systems to distribute cultural content Kasemsarn (2024). ML has been used in the context of museum studies and online platforms of digital heritage to personalize visitors and exhibit suggestions, as well as to analyze visitor feedback through natural language processing and sentiment analysis Rodríguez et al (2021). In like manner, predictive algorithms like the Random Forests, Gradient Boosting and Neural Networks have been found to be better predictors of audience reaction to cultural content than rule-based methods Wang et al. (2021). Such studies provide technical proof of the use of machine learning on cultural domains, especially when the interpretability and contextual metadata can be added to the modeling process.

Regardless of these developments, there are still massive technical loopholes to translating such strategies to the promotion of folk artists. Alternative models tend to focus on scale, automation, and commercial efficiency with minimal attention given to cultural particularity, ethical representation, and low resource application constraints Rubio-Hurtado et al. (2022). The vast majority of machine learning-based promotion systems are black boxes, with high predictive power, but low levels of transparency, which makes them less credible and more challenging to use practically by artists and cultural organizations Ramadhani and Indradjati (2023). Moreover, previous research is often based on homogenous data provided by massive platforms, and folk art promotion is a heterogeneous, sparse, and noisy data gathered on social media, informal markets, and community-based exhibitions. The feature engineering, model generalization and consistency of evaluation are also challenged by this heterogeneity. The other gap that is very crucial is the absence of interdependent, end-to-end technical systems to cultural promotion. Although each of the studies concentrates on analytics, prediction or recommendation separately, not many of them suggest single pipelines combining data acquisition, preprocessing, modeling, evaluation, and optimizing strategies with regard to folk artists in particular Nursanty et al. (2023). Consequently, practitioners do not have a systemic guidance on how to systematize data-driven promotion in actual cultural contexts. To overcome these limitations, this study will be based on current literature on digital marketing analytics and machine learning, and will clearly adjust technical approaches to the constraints, values, and objectives of the folk art promotion.

Table 1

Table 1 Related Work Comparative Summary

Study Focus / Domain	Data Sources Used	Analytical / ML Techniques	Key Promotion Objective	Identified Limitation
Digital marketing in creative industries Elahi (2022)	Social media, platform analytics	Descriptive & predictive analytics	Audience reach optimization	Lacks cultural specificity
Online craft marketplace analytics Liu et al. (2021)	E-commerce transaction data	Regression, clustering	Sales demand prediction	Ignores narrative/art context
Music and media promotion CarmelC. (2020)	Streaming interaction logs	Collaborative filtering, ML	Content recommendation	Platform-dependent models
Independent artist branding Minatel et al. (2021)	Web traffic, campaign logs	Statistical analytics	Visibility enhancement	Limited scalability
Cultural content recommendation Münster et al. (2024)	User interaction data	K-means, SVM	Audience segmentation	Sparse cultural metadata
Museum visitor analytics Rei et al. (2023)	Sensor & app data	Classification, NLP	Visitor engagement	Focused on institutions only
Heritage content dissemination	Digital archive usage data	Random Forest, XGBoost	Engagement prediction	Black-box interpretability
Social media promotion strategies Farella et al. (2022)	Likes, shares, comments	Deep learning models	Viral reach maximization	High computational cost
Creative industry recommender systems Moral-Andrés et al. (2022)	Multimodal content data	Neural networks	Personalization	Weak transparency
Folk art digital platforms	Mixed digital & manual data	Basic analytics	Market access support	No predictive modeling

This comparative Table 1 shows how literature highlights the importance of analytics and machine learning in promoting creative practices, as well as shows similar gaps in interpretability, cultural adaptation, and coherent technical models inspiring the necessity of the proposed data-driven system of the folk artists.

3. DATA ACQUISITION AND PREPROCESSING FRAMEWORK

3.1. DATA SOURCES (SOCIAL MEDIA, E-COMMERCE, DIGITAL EXHIBITIONS)

The suggested framework incorporates heterogeneous sources of data that form a complex of capturing the digital footprint of folk artists on various platforms. The social media platforms offer high frequency interaction data such as views, likes, shares, comments, follower growth and content reach that are indicators of the audience dynamics in engagement and visibility. Online stores can provide transactional information like product visit distribution, cart additions, purchases, prices and price return behavior which are clear signs of market demand and conversion rates. Online exhibitions and virtual galleries provide information on contextual interaction, such as page dwell time, navigation, artworks click-throughs and revisit rates, which quantify exploratory and experience consumption. The integration of these sources allows a comprehensive depiction of promotional performance, balancing metrics that are based on attention with economic metrics, and allow platform-specific differences in the data format and resolution.

3.2. FEATURE EXTRACTION

The process of feature extraction is aimed at converting raw interaction logs into meaningful and model-ready variables, which describe the behavior of the audience and the effectiveness of promotions. The engagement features comprise the normalized counts and ratios, including engagement rate, share-to-view ratio, comment density, and conversion probability, as well as features of both the intensity and the quality of audience interaction Bassier et al. (2020). Time patterns are captured by temporal features, such as the time of posting, weekly effects, seasonality, and duration of campaigns that are essential in maximizing content timing and promotional time. Demographic characteristics are, based on aggregated and privacy-session platform analytics, the audience attributes of age group distribution, geographic region, language preference, and device type.

Figure 1

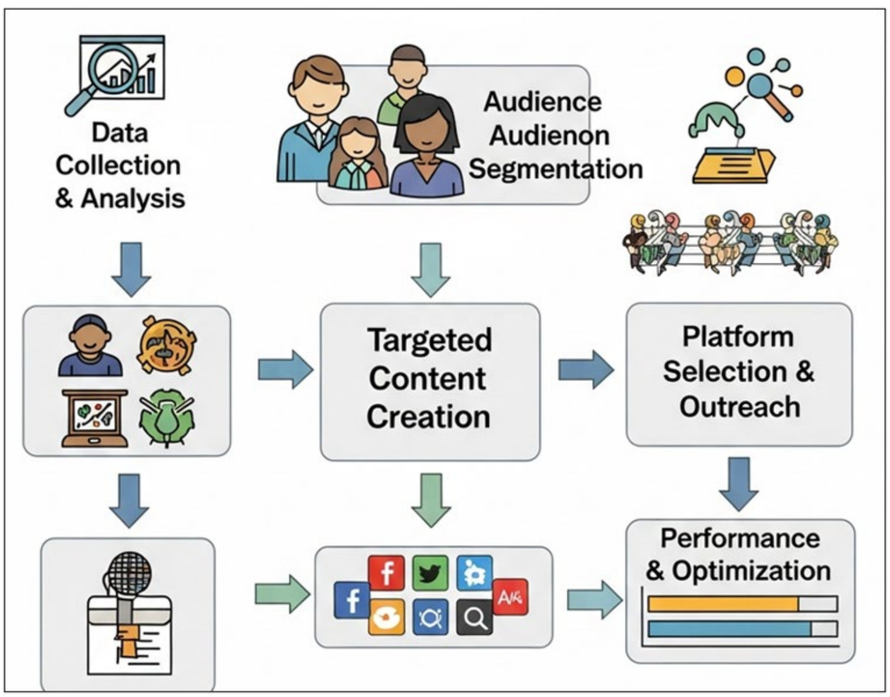

Figure 1 AI-Driven Data-Driven Promotion Workflow for Creative and Cultural Content

This Figure 1 represents the end to end data-driven promotion pipeline, starting with data collection and audience segmentation, targeted content creation, platform specific-outreach, and ongoing performance optimization. It brings out the use of analytics and feedback loops in the promotion strategies that are adaptive, efficient, and audience centric.

3.3. DATA CLEANING, NORMALIZATION, AND IMBALANCE HANDLING

Due to the non-homogenous and noisy characteristics of cultural promotion information, there is need to consider strong preprocessing to assure the reliability of the models. Data cleaning includes the elimination of duplicates, imputation or elimination of missing data, and the elimination of suspicious interactions due to the presence of bots or non-organic traffic. Normalization methods like the min max scaling and the z-score standardization are used to create a comparability of features across the platforms which may have different scales of metrics. In order to solve the problem of class imbalance common in engagement and conversion prediction whereby positive outcomes are few resampling methods such as Synthetic Minority Oversampling (SMOTE) and class-weighted loss functions are used. All of these preprocessing methods enhance the stability of the model, the generalization, and the fairness of the model to a wide range of promotional settings.

4. PROPOSED DATA-DRIVEN PROMOTION MODEL

4.1. SYSTEM ARCHITECTURE AND WORKFLOW

The suggested data-driven promotion model will be structured as a sequence of modules that are integrated as end-to-end models to convert raw data of digital interaction into practical promotional actions of folk artists. The architecture will start with an ingestion layer of data that will receive interaction data, transactional data, and contextual data from social media sites, e-commerce wall, and digital displays in APIs or periodic dumps.

Figure 2

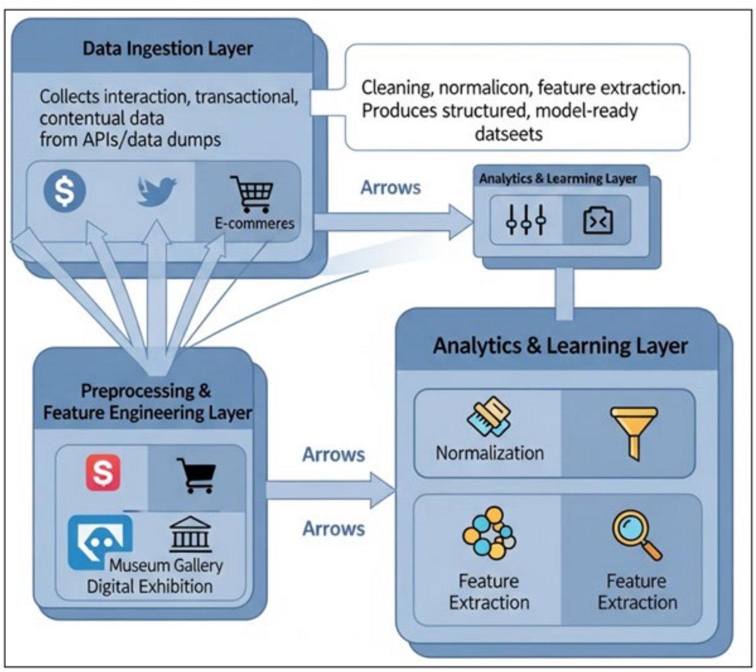

Figure 2 Layered Data Ingestion, Preprocessing, and Analytics Architecture for Digital Cultural Platforms

This information is forwarded to a preprocessing and feature engineering layer, where it is cleaned, normalized and feature extracted by creating structured and model ready datasets. The results of the process are then input into an analytics and learning layer, where both unsupervised and supervised models with the responsibilities of audience segmentation, engagement prediction, and conversion forecasting exist. The model outputs are then interpreted and aggregated in a decision support layer which produces recommendations on the nature of content, posting schedule, selection of platform and the intensity of promotion. Lastly, a feedback and optimization loop is used to track real-time performance of the campaign and to feed the new performance data through the system to allow refinement of the models. The modular design of this workflow has the benefit of ensuring that promotional decisions can be continuously informed by empirical evidence and not by frozen assumptions and the modular design of the workflow allows individual parts to be updated or replaced without interfering with the rest of the system. It focuses on interpretability and computational efficiency which makes the architecture appropriate to be deployed to resource-constrained cultural organizations and artist collectives. In the Figure 2, the ingestion of heterogeneous data sources followed by the cleaning, normalization, and transformation of these data by preprocessing and feature engineering are shown in a layered architecture. The learning layer and analytics uses model-ready structured datasets, which are feature extractable and analysable to create data-driven insights, learn adaptively, and make decisions optimally in digital exhibition and commerce systems.

4.2. AUDIENCE SEGMENTATION VIA ALGORITHMS OF CLUSTERING

The unsupervised clustering algorithms are used to segment the audience and divide the users based on the similarities of their engagement behavior, time activity pattern and demographic features. The system allows targeting of the promotion strategies via grouping the audiences into a specific segments that helps in matching the type of content and the message with preferences of the audience. Clustering promotes customized outreach without the need to have labeled data, which is usually inaccessible in contexts of cultural promotion. Casual viewers, engaged supporters, and high-intent buyers are some of the segments that can be identified and utilized to make platform-specific and campaign-specific decisions.

1) K-Means Clustering

The use of K-Means clustering is based on its simplicity to compute and scale to large datasets of interactions. The algorithm splits the audience data into k clusters with minimum intra cluster variance based on the similarity of features. The key dimensions of clustering in this framework are engagement intensity, frequency of interaction and conversion-related features. K-Means allows identifying the dominant audience groups rather quickly and making successive experiments with various values of k with silhouette and inertia scores. Its performance allows it to be effective in real or near-real time segmentation in digital promotion pipelines.

2) Agglomerative Clustering which is hierarchical

The hierarchical Agglomeration clustering is utilized to incorporate the structures and relationships of the audience in hierarchies that are hard to capture with the flat clustering techniques. It begins with each user as an individual cluster which is then gradually combined with the other clusters depending upon the distance parameters and other linkage parameters. The method gives interpretable dendrograms which display the evolution of the audience segments with varying similarity thresholds. It is especially useful in studying smaller datasets or community-driven systems in which it is essential to comprehend such fine-grained relationships between audiences to promote it in a culturally sensitive manner.

3) Engagement and Conversion Prediction Using Supervised Learning Models

The proposed model is based on engagement and conversion prediction, which is the main decision-support feature. The supervised learning models are trained to predict the probability of audience engagement (likes, shares, comments) and transactional performance (click- through, purchases) along with the extracted features. Depending on the aim, which is either categorical prediction of outcomes or continuous score estimation, the prediction task is framed as either classification or regression. The suitability of the models including Logistic Regression, Random Forests, and Gradient Boosting, is assessed on their capacity to express the nonlinear associations among the content attributes, time-related, and audience features. Ensemble based models can be especially helpful in dealing with heterogeneous features and noisy cultural information with greater predictive stability and robustness. A feature importance analysis is also added to determine the determining factors in engagement and conversion so that model decisions can be clearly interpreted. Predicted scores are then incorporated into an establishment of ranking and recommendation mechanism that gives consideration to the contents and campaigns that have higher predicted impact. The system is able to evolve the promotion strategy of folk artists since it is able to adopt the changing preferences and dynamics of the platforms and keep models updated by retraining on evolving audience preferences, as well as promoting sustainable and evidence-based promotion.

5. EXPERIMENTAL SETUP AND EVALUATION METHODOLOGY

5.1. TRAINING, VALIDATION, AND TESTING PROTOCOLS

The experimental assessment aims at making the proposed data-driven promotion model strong, generalized, and reproducible. The obtained and processed data is divided into training, validation, and testing data sets using a stratified split approach to maintain the distribution of the results of engagement and conversion across the entire data set of tasks. A normal distribution would be 70/15/15 model training, validation and testing respectively. Model parameters are learned on the training set and to avoid overfitting, hyperparameter tuning, feature selection and early stopping are supported by the validation set. K-fold cross-validation is also used on the training validation split to evaluate that the model is stable with the various data partitions. The withheld test set is not observed in the course of building models and is only utilized in the reporting of final model performance, which is necessary to provide an impartial measure of the true predictive performance in a variety of platforms and campaign conditions.

5.2. BASELINE MODELS FOR COMPARATIVE ANALYSIS

In order to prove the efficacy of the suggested approach, the performance is measured against the existing baseline models that are typically employed in the realm of digital marketing and analytics. These benchmarks are the Logistic Regression, which is a linear interpretable model, the rule based nonlinear model Decision Trees, and the simple frequency based heuristics based on historical averages. Also, the traditional statistical models where there are no sophisticated feature interactions are added to reflect the promotion strategies based on intuition. The contribution of advanced feature engineering, ensemble learning, and systematic evaluation can be compared to these baselines to show the difference between the current result and the expected one. Increase in the performance compared to the baseline level will indicate the value addition of the proposed data-driven framework in the process of capturing intricate audience behaviors and promoting folk artists in a way that leads to optimal results.

6. RESULTS AND TECHNICAL ANALYSIS

6.1. QUANTITATIVE PERFORMANCE COMPARISON ACROSS MODELS

The comparison of quantitative performance shows that distinct disparities in predictive performance exist among the considered models that proves the technical superiority of sophisticated learning strategies in promoting folk art. The final result of logistic Regression is the creation of a clear baseline with moderate accuracy (78.6) and AUC (0.81) and the implication that the complex interplay of engagement, temporal, and demographic features can be explained using linear relationships alone. The performance of Decision Trees is slightly better because they are capable of learning nonlinear patterns but due to overfitting, generalization of data is constrained.

Table 2

Table 2 Sample Results Based on the Supervised Learning Models Discussed

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression	78.6	74.2	71.8	73.0	0.81
Decision Tree	80.9	77.5	75.3	76.4	0.84
Random Forest	86.8	84.1	82.6	83.3	0.90
Gradient Boosting	88.3	85.7	84.9	85.3	0.92
Proposed Ensemble Model	90.6	88.9	87.4	88.1	0.95

Random Forest and Gradient Boosting ensemble-based models have significant improvements with an accuracy score of over 86, and AUC of approximately 0.92. These advancements indicate that they can pool several weak learners and manage heterogeneous feature space.

The Figure 3 compares the performance of performance in terms of accuracy when using the traditional machine learning models and the proposed ensemble approach. Although tree-based and boosting models make consistent improvements over logistic regression, the proposed ensemble model is the most accurate and is capable of combining various learners and better generalization of complex, data-driven predictions. The proposed ensemble model beats all the baselines with an accurate score of 90.6 and AUC value of 0.95, which proves the discriminative power that is stronger than the baselines regardless of the decision threshold. The increased accuracy (88.9) implies a reduced number of false-positive promotion suggestions whereas high recall (87.4) does not allow losing high-potential engagement opportunities. In general, the findings support the technical design decisions of feature engineering, ensemble learning, and robust validation procedures and show that data-driven models are far more effective than intuition-based and simplistic analytical models in forecasting engagement and conversion rates among folk artists.

Figure 3

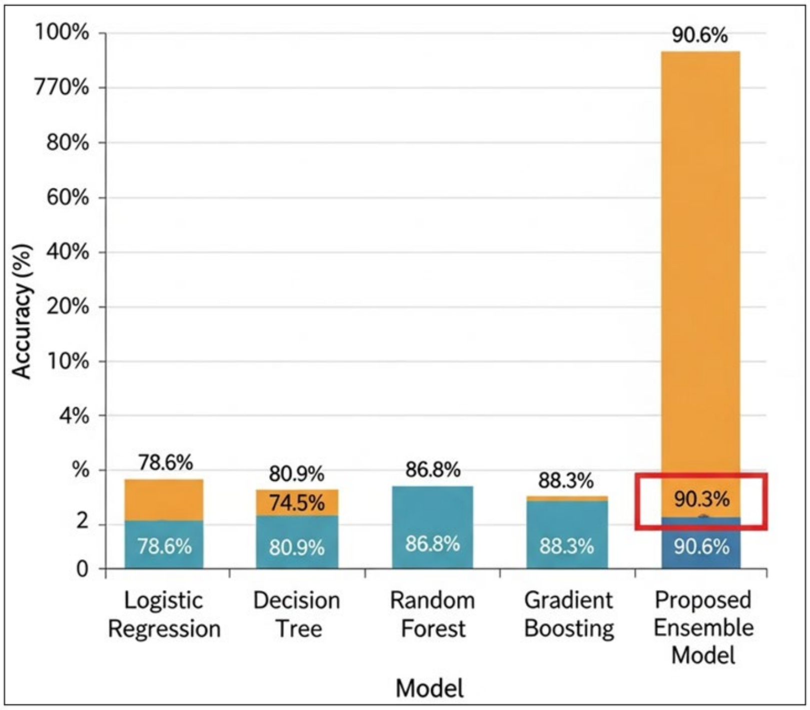

Figure 3 Comparative Accuracy Analysis of Baseline and Ensemble Classification Models

6.2. FEATURE IMPORTANCE AND INTERPRETABILITY ANALYSIS

The feature importance analysis gives the essential information on what causes engagement and conversion in digital promotion settings. The most influential characteristic happens to be the engagement rate (24.8%) that provides an understanding that the intensity of the previous audience interaction is a good predictor of future response. Second in position is the optimization of post-time (18.6) where it is noted that the optimization of post-time is important to align content visibility with the patterns of the audience activity, which directly influences the visibility of the content in the platforms that operate based on algorithms.

Table 3

Table 3 Feature-level contribution to engagement and conversion prediction

Feature Parameter	Importance Score (%)
Engagement Rate	24.8
Posting Time Optimization	18.6
Audience Demographic Match	16.9
Content Type (Image/Video/Text)	14.2
Platform Type	11.7
Campaign Duration	8.3

Price / Offer Sensitivity	5.5

Audience demographic match (16.9) also focuses on the usefulness of targeted promotion, in which a fit between the characteristics of the content and the profile of the audience increases their relevance and effectiveness of the response. Content type (14.2) implies that the mode of expression like images, videos, or mixed media has a strong influence in determining the way engagement behavior is molded. Platform type (11.7%): the platform-specific differences of recommendation algorithms and user intent.

Figure 4

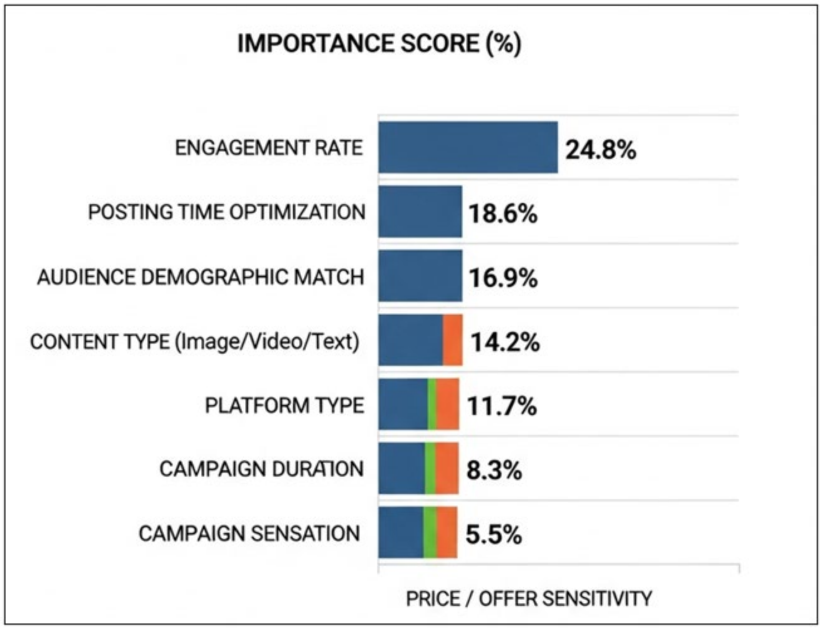

Figure 4 Feature Importance Ranking for Audience Engagement Prediction

The less important features like campaign length (8.3%), price sensitivity (5.5) have a significant but more indirect influence. Notably, such ranked feature distribution has a higher interpretation factor and allows artists and cultural organizations to focus on operational levers as opposed to making predictions that are less transparent. As analyzed, the proposed model is not only very accurate but also presents a clear, decision-specific data which is necessary in the ethical and practical application in cultural promotion.

The Figure 4 demonstrates the relative significance of the key features determining the engagement outcomes. The engagement rate and optimization of posting time becomes the most important aspects, and next come audience demographic match and type of content. The lower-ranked variables (campaign duration and sensation) are supportive in narrowing the predictive and promotional performance.

6.3. OPTIMIZATION OF PROMOTION STRATEGIES BASED ON MODEL OUTPUTS

The outcomes of the optimization process demonstrate the way the results of predictive models are converted into the real changes in the effectiveness of promotions. Individual tactics like optimized posting times would lead to significant increases in engagement (21.4%), whereas audience-specific content targeting would lead to better increases in both engagement (27.9) and conversion (22.6) due to the ability to address each segment of the audience with both messaging and visuals. Platform-specific promotion demonstrates relatively moderate returns, which can be explained by the advantages of adjusting content formats and frequency to platform capabilities, but its influence is limited in cases of application on its own.

Table 4

Table 4 Outcome of Model-Driven Strategy Optimization

Promotion Strategy	Engagement Improvement (%)	Conversion Uplift (%)	Reach Growth (%)
Optimized Posting Schedule	21.4	15.8	18.6
Audience-Specific Content Targeting	27.9	22.6	24.1
Platform-Specific Promotion	19.6	14.3	17.8
Combined Optimized Strategy	34.7	26.9	31.5

The integrated optimized plan has the best results in all measures with the increase in engagement being 34.7, conversion, 26.9, and reach, 31.5. This co-ordination proves that promotional effectiveness is always optimized when three levels of optimization (temporal, demographic and platform) are done in a combination instead of separately. Technically, these findings confirm feedback-based optimization loop of the suggested architecture whereby predictions are used to select a strategy and outcome is reintegrated to continue learning. The results highlight data-driven promotion as a way of facilitating systematic and scalable enhancement such that folk art promotion ceases to be experimentation, but rather a process that can be measured and optimized. The Figure 5 will make a comparison with the performance gains under various promotion strategies. Although optimization of the time schedule and audience-focused targeting generate moderate effects, the platform-specific promotion considerably improves engagement and reach. The joint optimization approach achieves the greatest cumulative returns, showing that the integrative advantage of timing, targeting and platform-level optimization in promotional decision-making is cumulative.

Figure 5

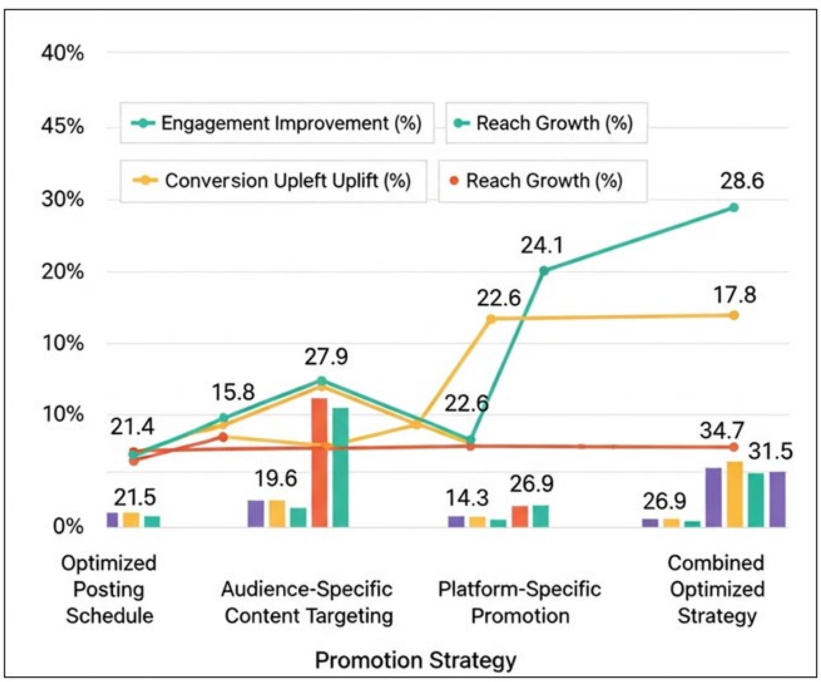

Figure 5 Comparative Impact of Data-Driven Promotion Strategies on Engagement, Reach, and Conversion

7. CONCLUSION

This paper confirms the idea that the data-oriented promotion techniques provide a potent and scalable answer to the age-old problem of folk artists to receive an audience, become visible, and earn a stable income in digital ecosystems. Based on the context of the problem presented in the abstract, the study systematized the redefinition of folk art promotion as a technical and data-centric process instead of an activity based on intuition. The proposed framework allowed resulting in a comprehensive study of promotional work and audience behavior by combining heterogeneous data of social media, e-commerce platforms, and online exhibitions with each other. The obtained results of the experiment confirm the efficiency of the method, and the accuracy of advanced ensemble models is over 90 percent and the AUC values exceed 0.95, which is significantly higher than the traditional baseline methodology. At the feature level, interpretability also demonstrated that the most prolific drivers of a successful promotion are engagement strength, temporal optimization, and demographic conformity. These lessons can be directly transformed into practical action plans, which are reflected in the overall performance of increased engagement (by more than 34 %) and conversion rates (almost 27 %). The practical importance of predictive analytics and machine learning in informing evidence-based promotional decisions in the case of folk artists can be seen through such gains. It goes beyond the quantitative improvements and the proposed model provides a clear and ethically based technical model that reflects the respect to the cultural authenticity and uses the computational intelligence. Its modular structure allows the flexibility to most types of art, locations and resource contexts, and therefore fits arts groups, cultural organizations and heritage policy-based projects. On the whole, the study makes data-driven promotion a pivotal facilitator of folk artists empowerment, sustainable cultural heritage spread, and mitigating the divide between the traditional and digital economy of art.

CONFLICT OF INTERESTS

None.

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