RESEARCH ARTICLE

Role of Temporal, Demographic, and Behavioral Factors in Customer Conversion Through Dynamic Creative Optimization in the Consumer-Packaged Goods Setting

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ABSTRACT

This study investigates the application of Dynamic Creative Optimization (DCO) in a Consumer-Packaged Goods (CPG) e-commerce setting, with the goal of discerning the most effective factors—temporal, demographic, and behavioral—on enhancing customer conversion. To evaluate this, an experiment was conducted over 35 days. Visitors to a CPG e-commerce site encountered one of three different Product Listing Pages (PLPs), each employing a distinct variant of DCO over the 35 days. Temporal-Based DCO adjusted content in real-time based on the timing of the visit, anticipating fluctuations in consumer intent. Demographic-Based DCO tailored the user experience to demographic information, presuming that a more relatable presentation would lead to higher conversions. Behavioral-Based DCO modified PLPs in accordance with individual browsing patterns and purchase history, operating on the premise that a user's past online activities could inform future interests. Data collected from these PLPs were analyzed using supervised machine learning to evaluate and predict conversion events from each. The findings revealed that PLPs with Behavioral-Based DCO demonstrated the highest conversion rates, affirming the significance of individual user behavior in optimizing e-commerce experiences. While demographic data also contributed positively to conversion rates, its effect was less pronounced than that of behavioral data, indicating the latter's superior predictive power. Temporal factors appeared to have the least influence, suggesting that the timing of dynamic content presentation alone may not be as critical as the substance of that content. The implications of these findings suggest a prioritization of behavioral data in DCO strategies to maximize the potential for customer conversions in the CPG e-commerce sector.

Keywords: Advertising Personalization, Consumer Behavior, Customer Conversion, Dynamic Creative Optimization, E-commerce, Machine Learning Algorithms, Product Listing Pages

INTRODUCTION

Over the past twenty years, the advertising industry has seen profound changes, especially with the advent of digital platforms. The transition from traditional forms of advertising to digital has altered the dynamic between the advertiser and the consumer. In the early days, advertising was a broadcast medium, with a one-size-fits-all approach that cast a wide net in hopes of catching a few relevant consumers [1], [2]. Now, advertising has shifted toward a model that privileges individual consumer data to craft personalized messages. This targeting allows advertisers to engage with individuals based on their unique preferences, behaviors, and demographic information. The ability to collect and analyze vast amounts of data through online interactions has empowered advertisers to create personalized advertisements that are more likely to resonate with, and thus influence, the targeted consumers. This tailored approach seeks to increase the efficacy of advertisements by making them more relevant to the individuals they reach.

Malheiros et al., (2012) defined personalization as "the inclusion of information in the ad content that identifies or characterizes the recipient" [3]. The rise of personalized advertising has been fueled by the continuous growth of online advertising and the accumulation of individual data. Advertisers have at their disposal an unprecedented volume of data points that can be used to understand consumer behaviors and preferences at an individual level. This allows for the customization of advertisements to match specific customer profiles, increasing the likelihood of consumer engagement [4]. Personalized ads can tap into the consumers' past interactions, search histories, and even social media activity to present products or services that the individual is more inclined to consider [5], [6]. By personalizing communication, advertisers can foster a more direct connection with the consumer, often resulting in a more efficient use of advertising budgets. Such targeted advertising can lead to tangible outcomes for brands, including measurable upticks in searches and interest for the products being advertised, underlining the potential returns on investment in personalized advertising strategies.

The effectiveness of advertising is significantly enhanced when the content is contextually relevant to the consumer. The concept of '*right place, right time'* is not just a catchphrase but a strategic component of modern advertising. Contextual advertising goes beyond simple personalization; it involves the alignment of ad content with the environment where the ad is displayed. This could mean placing sportswear ads on a fitness app or luxury goods ads in a high-end online magazine. The relevance of the advertisement to the consumer's current engagement increases the likelihood of drawing the consumer's attention and interest. When ads are in sync with the content the audience is already interacting with, there is a seamless connection that can improve the consumer's perception of the ad and the brand [7]–[9]. This connection can lead to a more impactful brand experience, as the audience feels the brand understands and aligns with their interests and current activities. This strategy capitalizes on the consumer's state of mind and situational context, potentially increasing the ad's influence and effectiveness.

DYNAMIC CREATIVE OPTIMIZATION (DCO)

Programmatic creative embodies a sophisticated approach to digital marketing, where algorithmic technology and data analytics converge to optimize advertising content [10]. It analyzes consumer data extensively, utilizing online behaviors and transactional histories to tailor advertisements to individual preferences and interests. Sophisticated software streamlines this process, ensuring that personalization occurs at a large scale. Unlike traditional advertising, which relies on a broad, static message, programmatic creative continuously refines the content based on real-time data, thereby maximizing the relevance of advertisements. This personalized strategy results in significantly enhanced engagement, as the marketing messages are more closely aligned with the target audience's inferred desires and requirements [11], [12].

Operational efficiencies in programmatic creative present a stark contrast to traditional ad production and management methods. Where previously a single creative was disseminated across multiple channels, programmatic creative employs automated systems to produce diverse ad variations tailored to distinct consumer segments [13], [14]. This approach not only boosts consumer engagement by offering personalized content but also addresses the issue of ad fatigue through constant updates and variations. Real-time adjustments to creative content, driven by performance data, lead to an advertising experience that is both engaging and non-intrusive for the consumer. These systems play a crucial role in maintaining the relevancy and freshness of advertisements through strategic content rotation, sequencing, and timely messaging updates [15], [16].

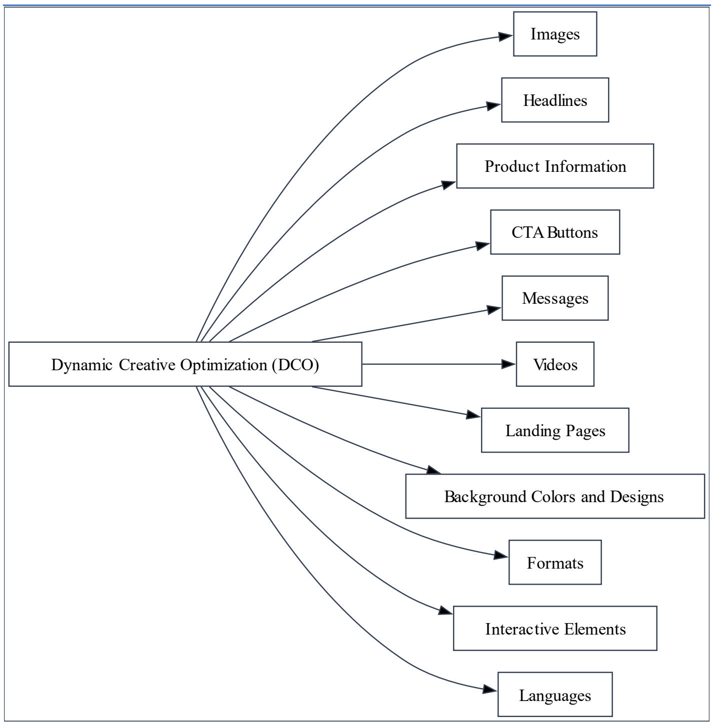
The efficacy of advertising in the programmatic creative space is further optimized through iterative message testing and continuous enhancement. Ad creatives undergo constant evaluation and refinement based on performance metrics and audience data, rather than waiting until the end of a campaign for assessment. Machine learning algorithms and data analytics enable controlled experimentation with creative variables, identifying the most effective elements of an ad campaign [17], [18]. This methodical, data-driven approach allows for an objective assessment of campaign elements, delivering insights into consumer behavior and preferences. The inherent adaptability of programmatic creative not only improves the current advertising efforts but also builds a repository of knowledge for future marketing strategies. This marks a shift from the retrospective campaign analysis to a model of ongoing optimization, aligning with the fluid and rapid pace of digital consumer engagement [12], [19].

Dynamic Creative Optimization (DCO) uses advanced display ad technology to craft personalized advertisements using real-time data about viewers at the moment ads are served [20]. This technology integrates data feeds, which may encompass a variety of user-specific information, to generate a multitude of creative variations. Each variation is constructed from multiple elements that can be altered, such as background and foreground images, headline text, messages, and calls to action. DCO not only automates the creation of these diverse ads but can also employ algorithms to enhance performance through multivariate testing. This allows for the systematic analysis of different creative components to determine which combinations perform best in terms of viewer engagement and conversion rates. Consequently, DCO provides a powerful tool for advertisers to maximize the relevance and effectiveness of their ad campaigns by ensuring that each viewer is presented with the most compelling visual and textual content.

The essence of DCO lies in precisely personalizing advertisements by manipulating various creative elements in real time and at scale. It enables the dynamic generation of ad content, with each layout populated with the appropriate assets for an individual user at the time the ad is created. Personalization can extend to virtually every aspect of an ad, including copy, images, videos, colors, and clickable links. Moreover, DCO campaigns can be disseminated across multiple digital channels—including display, video, and mobile platforms—ensuring a consistent and tailored advertising experience regardless of the device or medium. Targeting parameters for these ads can be based on a wealth of criteria ranging from geographic location and demographic data to more behavioral and lifestyle indicators. DCO can engage in personalized retargeting, presenting users with ads that reflect their specific interactions with the advertiser's site, thereby enhancing the potential for conversion [21].

The operational intelligence of DCO stems from its capacity to interpret a range of targeting variables that guide the generation of personalized ads. These variables are typically conveyed from a data management platform (DMP) to the DCO system, enabling the ad server to tailor content according to the information contained within them. However, DCO is not exclusively reliant on DMPs; it can also utilize other data sources, such as direct audience segmentation within the ad itself. This flexibility allows for the incorporation of various data types, such as geographic locations determined through IP addresses, to inform the customization process. Through the strategic utilization of these data streams, DCO optimizes the creative elements of ads to align with the user's context and characteristics, thus delivering a highly relevant and targeted advertising experience [22].

Figure 1. Components that can be dynamically altered in the creation of personalized ads through DCO



Dynamic Creative Optimization (DCO) is a transformative approach in digital advertising that enables brands to deliver hyper-relevant ads to users. DCO facilitates the tailoring of display campaigns to achieve maximum performance, thereby allowing brands to scale their unique advertising experiences. Smart messaging targets user-specific pain points, fostering a connection between the consumer and the brand, which not only enhances the digital presence of the latter but also elevates brand awareness. The sophistication of modern DCO solutions offers advertisers total creative control over ad layouts. Predictive AI algorithms fine-tune creatives in real-time, selecting the most suitable design elements based on an array of signals indicative of buying intent. This level of customization ensures that ads do not get lost in the digital clutter, but instead, stand out by resonating with the target audience's preferences, effectively extending the reach and impact of the brand [23].

The efficiency and cost-effectiveness of DCO are underscored by its fully automated decision-making process, which occurs in real-time with each ad impression served. This process adapts creative elements, such as images, layouts, calls-to-action (CTAs), and offers to align precisely with the audience's interests. The integration of connected data sets enables the optimization of creatives for each viewer, significantly reducing the time and resources required for manual conversion rate optimization (CRO) tasks. As a result, brands can allocate their budgets more efficiently, improve conversion rates, and drive a higher return on investment (ROI) for their advertising spend. Despite these advancements, it remains crucial for brands to continuously monitor ad spending and measure the efficacy of their campaigns to maintain a balance between targeted advertising and budgetary constraints [24].

The retargeting capabilities of DCO are particularly potent in e-commerce, where it can predict products of interest to the user, such as items left in an abandoned cart or previously viewed products. DCO refines retargeting campaigns by narrowing the focus of banner communications from potentially thousands of products to a select few that are most relevant to the user. This precision in ad content is critical for the performance of the campaign. DCO's ability to automatically optimize ad copy and imagery ensures the delivery of pertinent content, preventing the bombardment of users with irrelevant ads and keeping the brand at the forefront of potential customers' minds. Through this method, brands can efficiently leverage retargeting strategies to increase engagement and conversions without sacrificing the quality or relevance of their advertisements.

RATIONALE OF THE STUDY

In the Consumer-Packaged Goods (CPG) industry, the deployment of cutting-edge digital technologies is integral to marketing strategies, given the highly competitive nature of the marketplace. Advanced programmatic advertising methods offer targeting capabilities, driven by real-time data and sophisticated algorithms, which enable marketers to fine-tune their campaigns to individual consumer behaviors and preferences. In particular, the ability to customize the creative content of advertisements on-the-fly according to a range of triggers, such as demographic details, interaction history, and contextual information, provides a tool for increasing the relevance and effectiveness of advertising content. The ultimate goal of employing such technologies is to enhance the engagement between the brand and the consumer, thereby increasing the likelihood of conversion.

The integration of expansive data sets is crucial for the success of targeted advertising strategies in the CPG sector [25]. This requires the synthesis of comprehensive customer information and wide-reaching market intelligence to inform the decision-making process. The dynamic nature of consumer goods, characterized by fast-moving trends and the need for rapid stock turnover, makes the real-time aspect of data analysis especially valuable. By utilizing data-driven insights, CPG brands can optimize every aspect of a marketing campaign, from the positioning of the product in the advertisement to the timing and context in which it is displayed. These precise marketing efforts enable brands to achieve a more strategic allocation of their advertising budget, focusing on the most promising prospects and minimizing ineffective ad spend.

Moreover, the perishable nature of many CPG items demands that advertising campaigns be both agile and responsive. As such, the technology used must be capable of instantaneously adapting to changes in inventory levels, product updates, and time-sensitive promotions. This responsiveness is not just about mitigating losses by selling products before they reach their expiration but is also about capitalizing on opportunities that arise from sudden shifts in consumer demand or behavior. CPG companies can create a more dynamic and responsive advertising strategy that aligns closely with the fluid nature of consumer market trends and the logistical demands of product lifecycles.

The primary objective of this study is to evaluate the impact of Dynamic Creative Optimization (DCO) on customer conversion rates in the Consumer-Packaged Goods (CPG) e-commerce space. It aims to identify which factors among temporal, demographic, and behavioral are most influential in improving the efficacy of DCO. By systematically analyzing these variables, the study seeks to provide insights into how targeted creative content can be optimized to cater to individual consumer profiles. Additionally, the study intends to contribute to the strategic marketing tactics by determining the optimal application of DCO that could lead to higher engagement and sales in the CPG sector.

METHOD

The experiment was set within the context of a Consumer-Packaged Goods (CPG) e-commerce site and spanned a period of 35 days. The focus was to determine which of three different Product Listing Page (PLP) designs, each based on a variant of Dynamic Content Optimization (DCO), was most effective in driving conversions. The DCO variants included Temporal-Based, Demographic-Based, and Behavioral-Based designs.

The Temporal-Based DCO changed the PLP content in real-time, leveraging data such as the time of day, day of the week, seasonality, weather conditions, holidays or events, and sales cycles. The aim was to match the content with the presumed consumer intent linked to these temporal factors.

For the Demographic-Based DCO, the PLP was customized according to demographic factors including age, gender, income level, geographic location, household size, and education level. The underlying assumption was that a PLP which resonated with the user's demographic profile would be more effective in driving conversions.

Lastly, the Behavioral-Based DCO was programmed to alter the PLP in response to an individual's browsing patterns [26], purchase history, ad engagement, website navigation patterns, shopping cart abandonment, loyalty program membership, device usage, search queries, and social media activity. This approach was based on the premise that a user's past behavior is indicative of their future interests and preferences.

The collected data from user interactions with these PLPs were then analyzed using a combination of supervised machine learning and deep learning algorithms. The purpose of employing these advanced analytical methods was to precisely measure and understand the impact of each DCO approach on conversion events. The analysis would not only reveal which DCO variant led to the highest conversion rates but also provide insights into how temporal, demographic, and behavioral factors could be optimally combined for content optimization in the future [27].

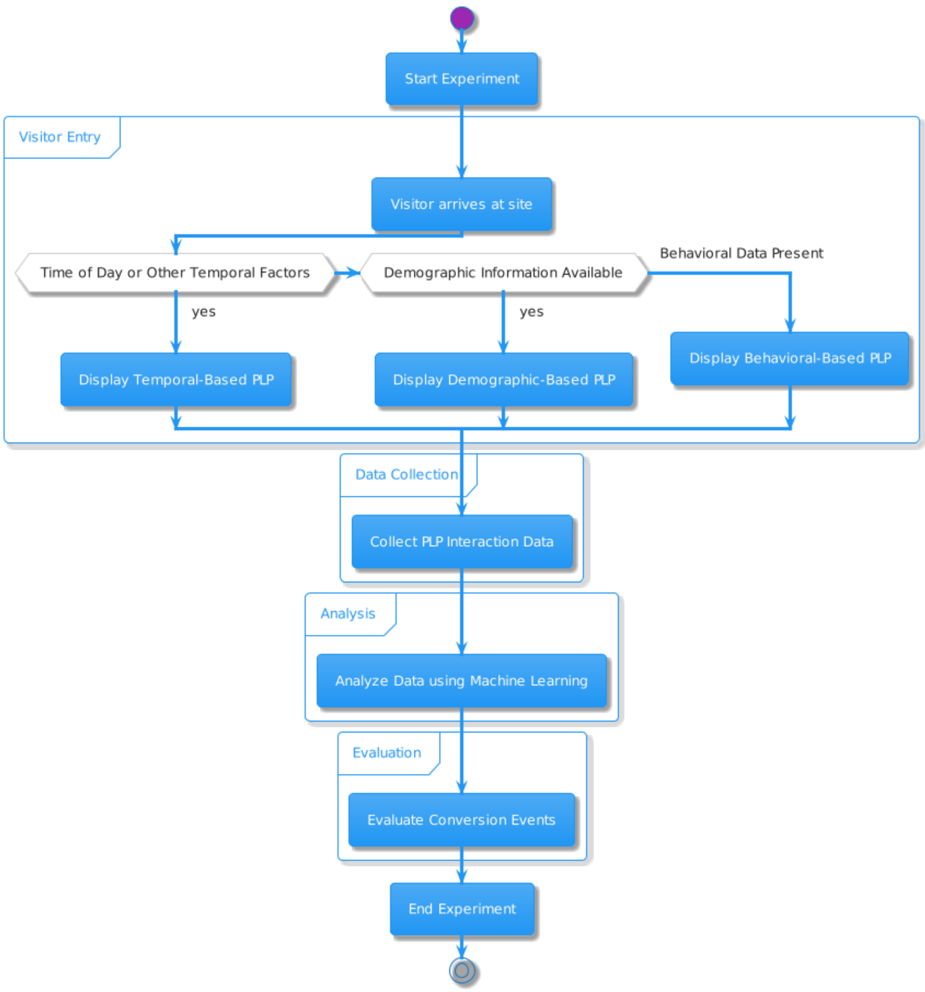
Table 1. Optimization items for temporal, demographic, and behavioral factors

Category	**Factors**	**Measurement/Description**
Temporal Factors	Time of Day	Hours and minutes, broken into time slots (6-9 AM for morning routine products).
	Day of the Week	Monday to Sunday, with noted peak days for engagement or purchase.
	Seasonality	Calendar seasons or specific periods (back-to-school season).
	Weather Conditions	Temperature (°C/°F), humidity, or events (rain, snow, sunny).
	Holidays or Events	Specified by date and nature (national holiday, cultural event).
	Sales Cycles	Time intervals for sales periods (bi-annual sales, quarterly clearances).
Demographic Factors	Age	Ranges for targeting (18-24, 25-34, etc.).
	Gender	Male, female, or spectrum; may not use gender targeting.
	Income Level	Low, middle, high income; estimated by zip code, profession, or purchase behavior.
	Geographic Location	City, region, country, or zip code/postal code.
	Household Size	Number of individuals in a household (1, 2-3, 4+).
	Education Level	Highest level of education completed (high school, undergraduate, graduate).
Behavioral Factors	Purchase History	SKU numbers, frequency of purchases, average spend.

Engagement with Previous Ads	Click-through rates (CTR), impressions, video views, interaction times.
Website Navigation Patterns	Pages visited, time on pages, frequency of visits tracked by cookies or similar technologies.
Shopping Cart Abandonment	Items left and frequency of abandonment incidents.
Loyalty Program Membership	Membership status or tier, points accumulated, redemption history.
Device Usage	Device type, operating system, device model from user-agent strings.
Search Queries	Keyword frequency, recency, and number of related searches.
Social Media Activity	Likes, shares, comments, follows, hashtag use related to specific products or categories.

A Decision Tree is a non-parametric supervised learning method used for classification and regression tasks. It is a representation of a series of decision rules that lead to a class or value [28]. The structure of a decision tree consists of nodes, branches, and leaves. The topmost node is known as the root node, which signifies the starting point of the decision process without an incoming edge. Each internal node denotes a test on an attribute, each branch represents the outcome of a test, and each leaf node represents a class label or regression value. The paths from root to leaf represent classification rules. In essence, a decision tree splits the data into subsets based on the value of input features, and this process is repeated recursively in a manner that the final result is a tree with decision nodes and leaf nodes. The key advantage of decision trees lies in their ease of interpretation and visualization, as they mimic human decision-making more closely than other algorithms and can be easily understood without statistical knowledge [29].

Figure 2. Model architecture



Random Forest builds upon the simplicity of decision trees to create a more accurate and robust predictive model. It operates by constructing multiple decision trees during the training phase and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random forests correct for decision trees' habit of overfitting to their training set, as they employ the principle of bagging, which is the combination of learning models to improve the overall result. In the training of random forests, each tree is grown on a different sample of the data. The sampling is done with replacement, known as bootstrapping, which means some samples may be used multiple times in a single tree. Additionally, random forests add an extra layer of randomness to model building by searching for the best feature among a random subset of features to split on at each node, contributing to diversity among the trees and resulting in a more generalized model.

XGBoost stands for Extreme Gradient Boosting and is an implementation of gradient boosted decision trees designed for speed and performance [30]. It is a highly sophisticated algorithm that has become popular due to its effectiveness in many machine learning competitions. XGBoost improves upon the traditional gradient boosting method by introducing advanced regularization (L1 and L2), which prevents overfitting and provides better performance. It is designed to be computationally efficient and flexible, supporting various objective functions, including regression, classification, and ranking. XGBoost also implements several enhancements in the boosting process, such as gradient-based one-side sampling and monotone constraints, that allow for better handling of various types of data and more efficient use of computing resources. It handles sparse data and can work with missing data by inferring their presence through learned patterns. XGBoost's ability to manage under-the-hood details like parallel processing and handling large datasets makes it an attractive choice for data scientists looking to achieve state-of-the-art results [31].

Gradient Boosting Machines (GBMs) are a family of powerful machine-learning techniques that have shown considerable success in a wide variety of practical applications. They build predictive models in a stage-wise fashion like other boosting methods but use gradients in the loss function to guide the learning process [32], [33]. A GBM trains many models in a gradual, additive and sequential manner. The key idea is to construct new base learners to be maximally correlated with the negative gradient of the loss function, associated with the whole ensemble. Each new model takes into account the mistakes made by the previous models and tries to correct them. This method allows the algorithm to improve where it is not performing well. GBMs often use decision trees as their base learners, which can handle heterogeneous features and interaction between features naturally. They are also fairly robust to outliers in the output space, depending on the loss function used. Due to their predictive power and flexibility to accommodate various different types of predictive modeling problems [34], GBMs are widely used in both industry and academic settings [35].

RESULTS

Tables 2 through 5, distinct aspects of each model's predictive ability are apparent. Table 2 outlines the decision tree's metrics, where it shows robust results, particularly in the recall for class 0 (Non-conversion), achieving 0.99, indicating its strength in identifying true negatives. Its precision for class 1 (Conversion) is noteworthy at 0.99, illustrating a high likelihood of correct predictions for conversions. The F1-Scores are closely matched for both classes, with class 1 marginally higher at 0.93 versus class 0's 0.92, suggesting a balanced precision-recall trade-off, particularly for conversions. The overall accuracy here is at a notable 0.92.

Table 2. Decision tree performance

	Precision	Recall	F1-Score	Support
Class 0 (Non-conversion)	0.86	0.99	0.92	1739
Class 1 (Conversion)	0.99	0.88	0.93	2324
Macro Average	0.92	0.93	0.92	2031.5
Weighted Average	0.93	0.92	0.92	4063
Accuracy				0.92

Table 3 presents the random forest model's results, which are closely aligned with the decision tree's, albeit with a marginally lower precision for class 0. It scores a high recall for class 0 and an identical F1-Score for class 1 when compared to the decision tree. Interestingly, the accuracy increases slightly to 0.923, and the macro and weighted averages are nearly identical, indicating a very consistent performance across the classes. The random forest model's slightly better balance is reflected in the macro average, which is at 0.923 compared to the decision tree's 0.92, suggesting a small yet potentially important advantage in overall performance.

Figure 3. Decision tree

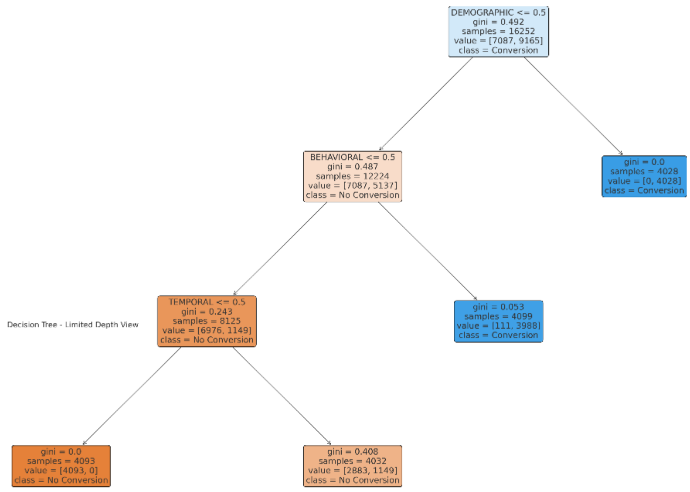


Table 4 examines the XGBoost model, which shows similar precision and recall metrics for the classes when compared to the random forest. The XGBoost has a comparable recall for class 0 and precision for class 1 but demonstrates a fractional improvement in accuracy at 0.9235. The macro and weighted averages of F1-scores are marginally higher than the random forest model, indicating incremental improvements in model performance. Finally, Table 5 depicts the Gradient Boosting Machines (GBM), which mirror the performance metrics of the random forest model. GBM scores equally on accuracy, with a 0.923 and closely matched macro and weighted average F1-scores. This parallel between the random forest and GBM suggests a possible convergence in performance for these ensemble methods, despite differences in their underlying algorithms.

Figure 4. Confusion matrix, ROC curve, and Precision-Recall-Curve in decision tree

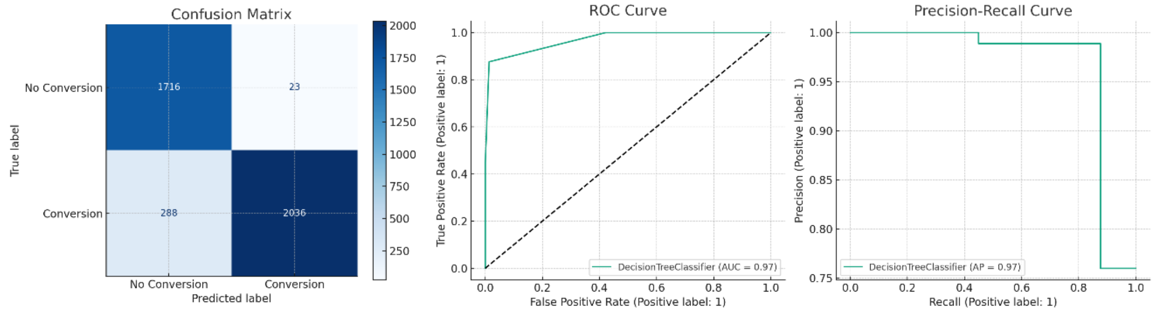
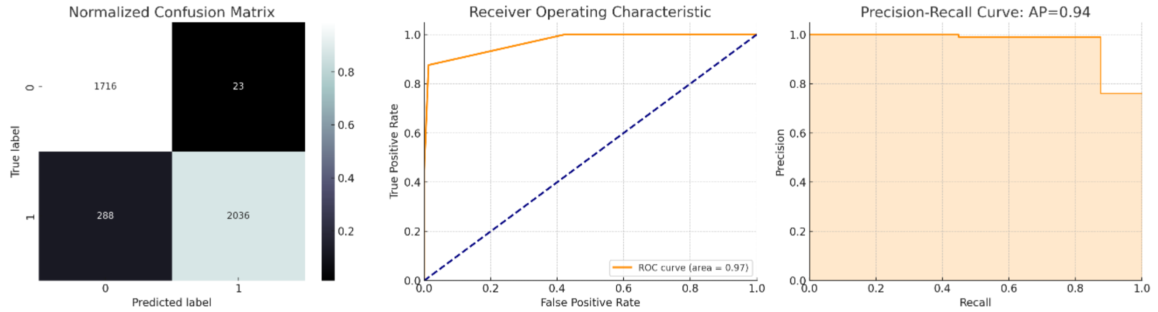


Figure 4 showcases the decision tree classifier's performance on the dataset. The Confusion Matrix indicates the classifier's ability to correctly identify a large number of instances for both classes, with a higher concentration of accurate predictions along the main diagonal. The ROC Curve suggests a favorable true positive rate across different false positive rate thresholds, implying effective class separation. The Precision-Recall Curve displays a high level of precision across varying levels of recall, indicating the classifier's ability to maintain a high rate of correct positive predictions as it captures a larger fraction of the actual positive cases.

Table 3. Random forest performance

	Precision	Recall	F1-score	Support
0 (Non-conversion)	0.856	0.987	0.917	1739
1 (Conversion)	0.989	0.876	0.929	2324
Accuracy			0.923	4063
Macro Avg	0.923	0.931	0.923	4063
Weighted Avg	0.932	0.923	0.924	4063

Figure 4. Confusion matrix, ROC curve, and Precision-Recall-Curve in Random forest



In figure 4, the confusion matrix reveals a high number of true positives and true negatives relative to false positives and false negatives, indicating strong model accuracy. The ROC curve's sweep toward the upper left corner and an area close to 1 suggests excellent discriminative power between the two classes. The Precision-Recall Curve complements this by showing a high level of precision across all levels of recall, which is particularly useful when the cost of false positives is high. The area filled under the Precision-Recall Curve indicates the model is effective at retrieving a high proportion of relevant instances while maintaining precision

Table 4. XGBoost model performance

	Precision	Recall	F1-score	Support
Class 0 (Non-conversion)	0.8563	0.9868	0.9169	1739
Class 1 (Conversion)	0.9888	0.8761	0.9290	2324
Accuracy			0.9235	4063
Macro Avg	0.9226	0.9314	0.9230	4063
Weighted Avg	0.9321	0.9235	0.9239	4063

Figure 5. Confusion matrix, ROC curve, and Precision-Recall-Curve in Random forest Gradient Boosting Machines

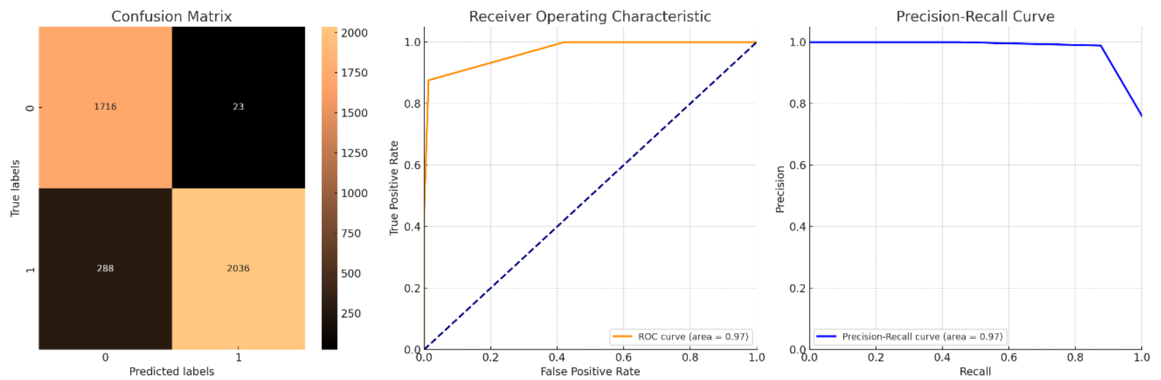


Table 5. Gradient Boosting Machines performance

	Precision	Recall	F1-score	Support
0 (Non-conversion)	0.856	0.987	0.917	1739
1 (Conversion)	0.989	0.876	0.929	2324
Accuracy			0.923	4063
Macro Avg	0.923	0.931	0.923	4063
Weighted Avg	0.932	0.923	0.924	4063

The model exhibits robust performance metrics, evidenced by the sub-plots in figure 5. The Confusion Matrix indicates a high number of true positives and true negatives, suggesting effective classification with relatively few errors given the low false positive and false negative counts. The ROC Curve, with its AUC close to 1, demonstrates strong discriminative ability, implying that the model distinguishes between the classes well. The Precision-Recall Curve further supports this with a high area under the curve, indicating that the model maintains a high precision across varying levels of recall, which is particularly beneficial in scenarios where the cost of false positives is high.

Figure 6. feature importance

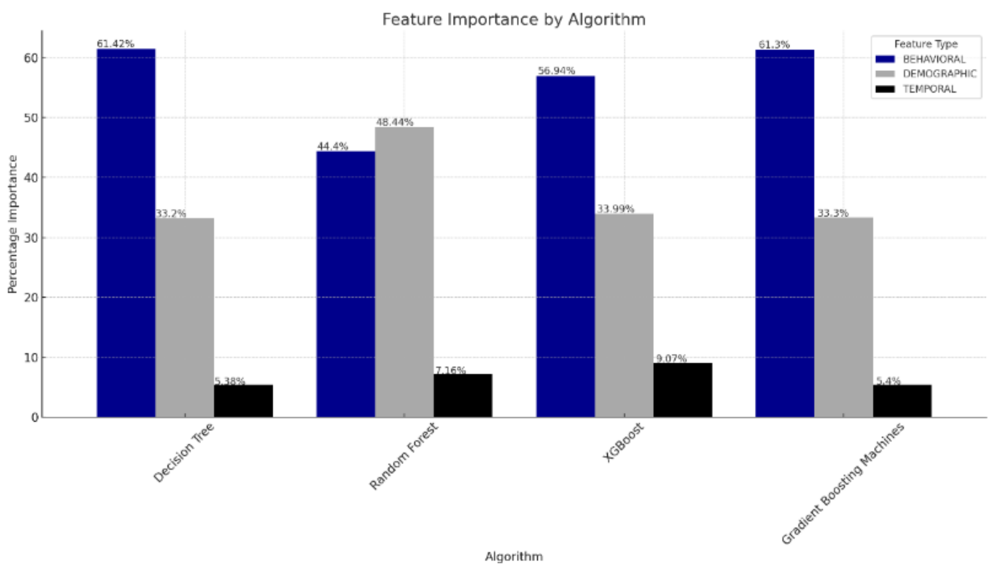


Table 6. feature importance

Algorithm	BEHAVIORAL	DEMOGRAPHIC	TEMPORAL
Decision Tree	61.42%	33.20%	5.38%
Random Forest	44.40%	48.44%	7.16%
XGBoost	56.94%	33.99%	9.07%
Gradient Boosting Machines	61.30%	33.30%	5.40%

Table 6 and figure 6 show the values of feature importance assigned by different algorithms, highlighting the perceived relevance of different types of data in predicting outcomes. The decision tree algorithm ascribed the highest importance to behavioral features at 61.42%, indicating a strong reliance on patterns of user behavior to make predictions. Demographic features followed with a significant 33.20%, while temporal features were deemed least important at 5.38%. This distribution suggests that for decision trees, understanding user behavior is paramount, but demographic context still plays a notable role. In contrast, the random forest algorithm distributed importance more evenly, elevating demographic features to the highest importance at 48.44%, followed by behavioral at 44.40%, and giving more weight to temporal features than the decision tree at 7.16%.

This implies a more balanced consideration of user attributes and a recognition of the temporal context in the random forest's predictive process. The XGBoost algorithm offered a middle ground between the two, with behavioral features still dominant at 56.94% but less so than in the decision tree, demographic features receiving a considerable 33.99%, and temporal features being given noticeably more importance at 9.07% than in the decision tree. The Gradient Boosting Machines presented an assessment of feature importance nearly identical to the decision tree, with a slightly lower attribution to behavioral features and a marginal increase for demographic and temporal features, indicating a consistent valuation of features with decision trees but with slight adjustments.

CONCLUSION

The findings of this study indicate that Product Listing Pages (PLPs) that utilize behavioral data to inform Dynamic Creative Optimization (DCO) strategies significantly outperform others in terms of conversion rates. This underscores the importance of individual user activity and interaction history in refining the e-commerce experience. By tracking consumer behaviors such as previous purchases and page interactions, DCO systems are able to adjust creative content in real-time to more closely match individual preferences. The research clearly demonstrates that personalization based on actual consumer behavior is more effective at converting browsers into buyers than other methods.

In contrast, demographic data, despite its role in tailoring advertisements, had a less substantial effect on conversion rates when compared to behavioral data [36]. This outcome implies that demographic information, which includes factors like age, gender, and location, does not have the same depth of insight into consumer behavior as direct behavioral analysis. Although demographic data provides a broad outline of consumer segments, it cannot match the detailed and specific customization that behavioral data can inform in DCO strategies.

Regarding the influence of temporal factors, the findings suggest that the specific timing of ad presentation is less critical to conversion rates than the content itself. This challenges the often-held belief that the timing of marketing efforts is a dominant factor in consumer engagement. The data suggests that what the content offers to the consumer is more influential in the decision-making process than when the content is presented [37]. Hence, while it is still important to consider timing, it should not overshadow the importance of content relevance in DCO strategies.

These findings carry strategic weight for marketers within the CPG e-commerce landscape, highlighting the need to focus on behavioral data when developing DCO strategies. Such an approach promises to more accurately anticipate and fulfill consumer needs, resulting in a more compelling online shopping experience. Tailoring content based on behavioral analytics offers an opportunity to more effectively prompt consumers towards making a purchase, optimizing the path from interest to action within the sales funnel. Consequently, for CPG companies seeking to enhance their online advertising performance, investing in advanced data analytics capabilities that provide insights into consumer behavior is essential. The strategic shift toward a behavioral data emphasis in DCO may serve as a factor in improving conversion rates and driving sustainable business success in the highly competitive CPG market.

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