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Promo Code Strategy in E-Commerce: A Literature Review on its Impact on Customer Churn Rate and Managerial Implications

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ABSTRACT

Promo codes are widely used in e-commerce as a digital marketing tool to increase customer acquisition and retention. However, recent studies question their long-term effectiveness, particularly in reducing customer churn. This study presents a systematic literature review (SLR) based on 123 peer-reviewed articles published between 2015 and 2024. The findings show that while promo codes can effectively boost short-term customer acquisition, their use without proper segmentation and loyalty integration may reduce long-term retention. The study emphasizes the need for data-driven strategies and alignment with customer relationship management (CRM) systems to improve customer loyalty. To support this analysis, several machine learning algorithms were applied, including Naïve Bayes, Decision Tree, and k-Nearest Neighbors (k-NN). Among these, the k-NN algorithm with k equal to 1 and Naïve Bayes yielded the highest predictive accuracy in identifying churn behavior. These insights offer practical guidance for e-commerce managers to design more effective and sustainable promo code strategies.

Keywords: Customer Churn; E-Commerce; Machine Learning; Marketing Strategy; Promo Code; SLR

INTRODUCTION

The e-commerce sector is fundamental to the worldwide economic transformation in the digital era (Tolstoy et al., 2021). The sector has expanded exponentially in the past decade due to technological advancements, enhanced accessibility, and increased transaction speed (Javaid et al., 2024). Due to intense rivalry, every company must employ marketing strategies that attract new clients while retaining existing ones (Dwivedi et al., 2021). A prevalent strategy is to provide promotional coupons or discount codes.

Promo codes serve as an incentive for consumers to complete transactions by offering immediate price reductions. This strategy has proven effective in increasing conversion rates, particularly among new users or during the launch of new products (Akin, 2024). In the context of e-commerce, promo codes have become a key element in pricing strategies, providing consumers with a more cost-effective shopping experience. However, the long-term effectiveness of promotional codes in fostering customer loyalty remains a subject of debate (Rashid & Kausik, 2024). While promotions can successfully attract new customers, they may also promote opportunistic behavior, where consumers make purchases only during discount periods. This tendency can increase the risk of customer churn and undermine efforts to build lasting customer relationships.

A critical indicator of a digital organization’s health is customer churn, defined as the steady attrition of clients (Park & Ahn, 2022). Elevated churn rates generally adversely impact long-term profitability and indicate a business’s inability to retain consumers (Ahn et al., 2006). An extensive, indiscriminate promo code may provide both advantageous and detrimental outcomes in this context. A business may forfeit a loyal and enduring customer base despite the ability to momentarily increase transaction volume. The escalating expenditure of acquiring new clients, referred to as Customer Acquisition Cost (CAC), significantly exceeds the cost of retaining existing clients, exacerbating the issue.

Furthermore, some studies advocate for a more data-driven and segmented strategy to be integrated with promotional campaigns (Nursalim et al., 2025). This approach allows enterprises to understand consumer behaviour better, identifying which clients are prone to loyalty and which are at risk of attrition (Tan et al., 2024). A systematic examination is necessary to ascertain whether the existing promotional code strategy effectively cultivates loyal customers or primarily contributes to attrition.

This research aims to systematically evaluate the literature on the relationship between customer turnover rate and the utilization of promotional codes. This article summarizes key findings from previous research and employs the Systematic Literature Review (SLR) methodology (Kamya & Marikannan, 2018) to identify gaps and inconsistencies. Ultimately, it formulates strategic recommendations for stakeholders in the e-commerce sector. This research is expected to facilitate the development of more sustainable digital marketing strategies and managerial practices.

Consequently, to understand the pattern of consumer behavior concerning the utilization of promo codes and its impact on churn propensity, a more sophisticated data-driven approach is necessary, such as implementing machine learning (Matuszelański & Kopczewska, 2022). This study examines the managerial implications of utilizing promo codes and their impact on customer attrition through a systematic analysis supported by machine learning techniques (Sauer et al., 2025).

LITERATURE REVIEW

Promo Code in Digital Marketing Strategy

Businesses utilize promotional codes as a pricing incentive to attract consumers, especially on digital platforms (Hammouri et al., 2022). This strategy incentivizes clients to buy by providing a time-limited discount (Japutra et al., 2025).

Conduct of direct acquisitions (Peña-García et al., 2020; Xie et al., 2016). Promo codes are commonly utilized in e-commerce during major promotional events such as Black Friday, Harbolnas, or the launch of new products. Due to their monitorable nature and direct correlation with consumer behavior, including purchase frequency and transaction value, promo codes are considered more quantifiable (Zhang et al., 2019).

Promotional coupons effectively enhance short-term conversions; nevertheless, certain studies suggest they do not consistently lead to increased customer loyalty. Excessive or poorly segmented promotions may lead customers to perceive that discounts are perpetual, resulting in a diminished appreciation of the product's actual value and reluctance to purchase in their absence (Nayal & Pandey, 2020). This raises significant doubts about the efficacy of promo codes as a long-term consumer retention strategy.

The Concept of Customer Churn in E-Commerce

Customer churn refers to the behavior of consumers who cease using services or fail to make repeat purchases within a designated period (Gordini & Veglio, 2017). Churn indicates that a business is struggling to forge enduring customer relationships in the highly competitive e-commerce industry. Churn control is a crucial aspect of digital firm strategy, as retaining existing customers is more economically advantageous than acquiring new ones (Kumar & Shah, 2004).

According to Choi & Sayedi (2023), aggressive promotional strategies such as offering large quantities of promo codes can increase sales by up to 27% after the campaign. However, this shows that customers attracted by promotions do not always become loyal buyers. Sharma and Pillai (2003) explain that these customers are mostly transactional, focusing only on short-term benefits rather than building a long-term relationship with the brand. Similarly, Jaiswal et al. (2018) found that the impact of such promotions is often temporary.

Customer Loyalty and Ongoing Promotion

Consistent experience, satisfaction, and a continual perception of worth are the cornerstones of client loyalty. Promotional tools such as promo codes can be integrated into a loyalty strategy via exclusive offers or points-based loyalty programs (Cardoso et al., 2022) (Nishio & Hoshino, 2024). Promotions, however, might jeopardize built loyalty if managed ineptly and without consideration of customer behaviour. To determine eligibility for specific promotions, it is essential to utilize data analytics and client segmentation (Barrera et al., 2024).

A developing strategy that numerous enterprises are adopting is the integration of promotional codes with customer relationship management (CRM) systems. Promotions under this technique are exclusively available to clients who demonstrate churn or possess a high customer lifetime value (CLV) (Xue et al., 2021). This is the intersection of loyalty efficacy and promotional efficiency (Meyer-Waarden, 2007).

Implications for E-Commerce Management

The integration of machine learning into promotional decision-making presents notable managerial implications. According to Ghosh et al. (2022), machine learning technologies enhance the ability to analyze consumer behavior and optimize promotional targeting. Haleem et al. (2022) further emphasize that machine learning-based churn prediction techniques support customer retention by identifying at-risk customers and preventing unnecessary marketing efforts toward already loyal clients. This approach enables organizations to balance customer acquisition and retention strategies more effectively, ensuring profitability while reducing customer attrition due to excessive or poorly timed discounts (Lemmens & Gupta, 2020).

Research Gap

Limited previous research examines the enduring impacts on customer loyalty and attrition, whereas certain studies emphasize the technical features of promotions' efficacy in enhancing sales. Moreover, few research explicitly links data-driven managerial techniques with discount coupons. This study investigates the effect of promo codes on customer attrition by analyzing data from global scientific publications and demonstrates how the results may be effectively utilized in managerial decision-making.

RESEARCH METHOD

Systematic Literature Review Approach

This study adopted a Systematic Literature Review (SLR) methodology to identify, evaluate, and synthesize existing research on the relationship between promotional code utilization and customer churn in the e-commerce sector. The SLR approach offers a rigorous and structured framework for collecting and critically assessing empirical evidence (Sivarajah et al., 2017; Kitchenham & Brereton, 2013).

Inclusion and Exclusion Criteria

To ensure the quality and relevance of the reviewed literature, specific inclusion and exclusion criteria were applied. Studies were included if they were peer-reviewed journal articles, available in full-text, and provided either empirical data or conceptual analysis related to promo codes, customer churn, or customer loyalty within the e-commerce context. Conversely, studies were excluded if they were editorials, opinion pieces, or non-academic in nature, focused solely on offline promotional activities, or were duplicated or not accessible in full-text format.

Study Selection Procedure

The study selection process adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol and was conducted in four key stages. During the identification phase, 123 articles were initially retrieved using predefined keywords. In the screening stage, 48 articles were excluded based on title and abstract assessments due to irrelevance to the research focus. The eligibility stage involved a detailed review of 45 full-text articles, applying the established inclusion and exclusion criteria. Finally, 15 articles were deemed suitable and selected as the primary sources for in-depth analysis. A PRISMA flow diagram illustrating the entire selection process is provided in Figure 1.

Analysis Technique

The selected studies were examined using a thematic synthesis approach consisting of data extraction, categorization, and synthesis. Key information such as author, year of publication, research objectives, methodology, and main findings was systematically

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coded during the data extraction phase. Subsequently, the studies were categorized into central themes, including the effectiveness of promo codes, their impact on customer churn, and related managerial strategies. The synthesis phase involved comparing the extracted data to identify recurring patterns, conflicting results, and research gaps. This analytical framework facilitates a comprehensive understanding of the interaction between promotional codes and digital marketing strategies in influencing customer behavior and retention.

Data Collection and Preparation

In addition to literature synthesis, a dataset of 1,486 simulated data points was constructed to support empirical evaluation. The dataset includes variables such as Customer ID, Transaction Date, Promo Used, Promo Value, Amount Spent, and Churner. Out of the total, 511 records were labeled as churned (true), while 975 records were labeled as non-churned (false). The summary of the data distribution is provided in Table 1.

Table 1. Transaction Data Collection Sample

No	Customer ID	Transaction Date	Promo Used	Promo Value	Amount Spent	Churned
1	CUST0000	2024-06-05T00:00:00+08:00	TRUE	10	29.67	TRUE
2	CUST0000	2024-03-02T00:00:00+08:00	TRUE	10	75.22.00	TRUE
3	CUST0000	2024-01-18T00:00:00+08:00	TRUE	5	101.99	TRUE
4	CUST0000	2024-04-27T00:00:00+08:00	TRUE	15	88.54.00	TRUE
5	CUST0001	2024-07-05T00:00:00+08:00	TRUE	0	26.83	TRUE
6	CUST0001	2024-05-19T00:00:00+08:00	TRUE	15	103.01.00	TRUE
7	CUST0002	2024-10-22T00:00:00+08:00	TRUE	0	103.67	FALSE
8	CUST0002	2024-06-20T00:00:00+08:00	TRUE	5	79.54.00	FALSE
9	CUST0002	2024-09-16T00:00:00+08:00	FALSE	0	81.98	FALSE
10	CUST0003	2024-02-25T00:00:00+08:00	TRUE	10	81.25.00	TRUE
.						
.						
.						
1486	CUST0499	2024-08-06T00:00:00+08:00	TRUE	10	108.590	TRUE

Note: Dates were formatted to YYYY-MM-DD for readability. Decimal errors in monetary values were corrected.

Quantitative Analysis and Predictive Modeling

To complement the systematic literature review, this study employs a quantitative approach combined with data mining techniques to predict customer churn within an e-commerce context. The research utilizes a dataset consisting of 1,486 transaction records containing variables such as Customer ID, transaction date, promotional code usage, promo value, total spending, and churn status. Out of the total data points, 511 indicate churn, while 975 represent retained customers.

Three machine learning classification algorithms—Naïve Bayes, Decision Tree, and K-Nearest Neighbors (KNN)—are applied to develop predictive models. These algorithms were selected based on their frequent usage in churn prediction research and their ability to handle both categorical and continuous data.

Research Stages

Data Collection

The dataset was compiled from simulated e-commerce transactions and supplemented by survey responses. Variables collected include demographic indicators, transaction frequency, promo code usage, transaction value, and churn status (defined as discontinuation of platform usage).

Data Preprocessing

The data underwent cleaning to remove duplicates and handle missing values. Unnecessary features were excluded, and the target variable, churn, was binary encoded (churn = 1; no churn = 0). Normalization was applied to numerical features to ensure consistency across variables.

Data Splitting

The cleaned dataset was split using k-fold cross-validation to ensure robust model training and evaluation. Training and testing sets were used to assess each algorithm's performance.

Model Integration and Comparative Analysis

Each classification algorithm was implemented and evaluated based on key performance metrics, including accuracy, precision, recall, and F1-score. A comparative analysis was conducted to identify the most effective model in predicting customer churn. Preliminary results indicate that k-NN (k=1) and Naïve Bayes produced superior predictive accuracy. These insights provide actionable intelligence for e-commerce managers aiming to refine their promotional strategies and enhance customer retention.

RESULTS

Based on the study selection procedure detailed in the methodology section, a total of fifteen scientific publications were selected for in-depth analysis. These studies employed diverse research methodologies, including quantitative analyses, field experiments, and predictive modeling using machine learning. All selected articles were published in reputable journals within the fields of digital marketing, e-commerce, and customer relationship management.

Characteristics of the Selected Studies

Of the fifteen studies reviewed, ten articles (66.7%) adopted a quantitative approach by analyzing survey responses or transactional datasets. Three studies (20%) utilized A/B testing or real-world promotional campaign experiments to evaluate the impact of promo codes. The remaining two studies (13.3%) applied predictive modeling techniques such as decision trees and logistic regression to forecast customer churn behavior.

The majority of the empirical data in these studies were drawn from prominent e-commerce platforms including Amazon, Shopee, Alibaba, and selected regional marketplaces. On average, the observational periods for data collection ranged from six

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months to two years, providing a robust temporal context for evaluating the effectiveness and limitations of promotional strategies.

Key Findings Related to Promo Codes and Customer Churn
Thematic analysis of the selected studies revealed three prominent patterns regarding the relationship between promotional code usage and customer churn.

First, promo codes are effective in boosting short-term conversions. Thirteen out of fifteen reviewed articles reported that the implementation of promo codes during promotional campaigns significantly increased customer transactions. For example, Zhang et al. (2019) documented a 38% increase in sales during a seven-day discount campaign. However, these gains were often short-lived and did not consistently translate into sustained customer engagement.

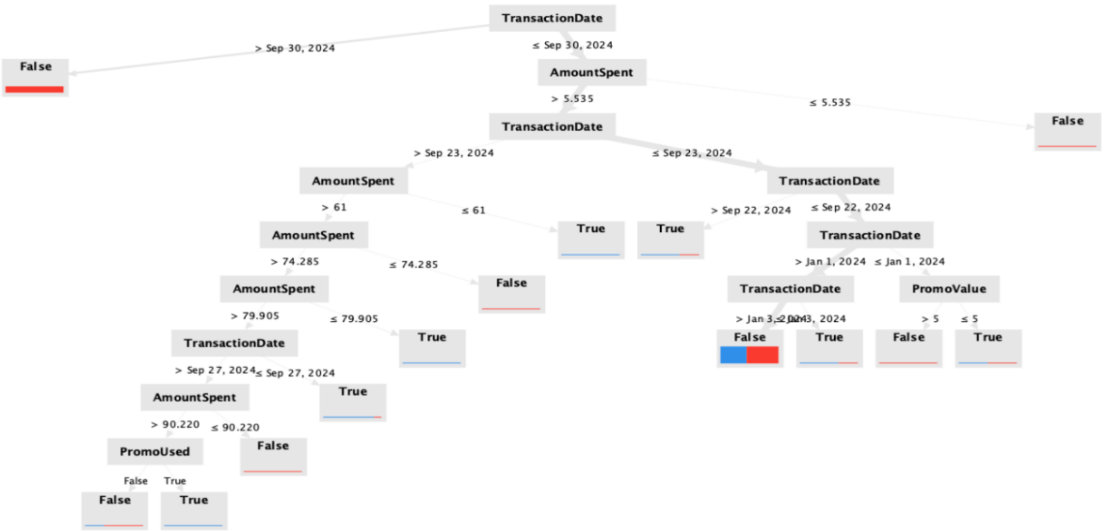
Second, promo codes do not guarantee long-term customer loyalty. Nine studies concluded that customers attracted primarily by discounts are more prone to discontinue purchases after the promotional period ends. Choi & Sayedi (2023) found that the churn rate increased by 27% within 30 days following a discount event, particularly among first-time buyers who did not return after their initial transaction.

Third, segmentation and personalization significantly enhance campaign effectiveness. Targeted deployment of promo codes, especially among at-risk customers, was shown to improve retention. Nguyen et al. (2019) reported a 15% decrease in churn when personalized promo codes were offered to customers identified as likely to leave, compared to undifferentiated mass campaigns.

Managerial Implications from Selected Studies
The findings yield several key insights for managerial decision-making in e-commerce operations. First, promo codes should be viewed as tactical instruments for specific short-term objectives rather than as core long-term retention strategies. Second, the integration of customer behavior analytics is essential for designing efficient promotional mechanisms. Third, data-driven loyalty programs that provide continuous value are more effective at reducing churn than sporadic discount-based incentives. Fourth, A/B testing and experimental validation are critical before implementing large-scale campaigns, to minimize unintended consequences such as increased post-promotion attrition.

Preliminary Machine Learning Results
The results of machine learning analysis in this study offer empirical reinforcement for the observed patterns. The initial implementation of classification algorithms such as Decision Tree, Naïve Bayes, and k-Nearest Neighbors (k-NN) revealed distinct differences in predictive accuracy. Detailed outcomes for each algorithm will be presented in the subsequent section.

Figure 1. Decision Tree Results



Tree

```
TransactionDate > Sep 30, 2024: False {True=0, False=368}
TransactionDate ≤ Sep 30, 2024
|   AmountSpent > 5.535
|   |   TransactionDate > Sep 23, 2024
|   |   |   AmountSpent > 61
|   |   |   |   AmountSpent > 74.285
|   |   |   |   |   AmountSpent > 79.905
|   |   |   |   |   |   TransactionDate > Sep 27, 2024
|   |   |   |   |   |   |   AmountSpent > 90.220
|   |   |   |   |   |   |   |   PromoUsed = False: False {True=1,
False=2}
|   |   |   |   |   |   |   |   PromoUsed = True: True {True=2,
False=0}
|   |   |   |   |   |   |   AmountSpent ≤ 90.220: False {True=0,
False=2}
|   |   |   |   |   |   TransactionDate ≤ Sep 27, 2024: True {True=7,
False=1}
|   |   |   |   |   AmountSpent ≤ 79.905: True {True=3, False=0}
|   |   |   |   AmountSpent ≤ 74.285: False {True=0, False=2}
|   |   |   AmountSpent ≤ 61: True {True=4, False=0}
|   |   TransactionDate ≤ Sep 23, 2024
|   |   |   TransactionDate > Sep 22, 2024: True {True=2, False=1}
|   |   |   TransactionDate ≤ Sep 22, 2024
|   |   |   |   TransactionDate > Jan 1, 2024
|   |   |   |   |   TransactionDate > Jan 3, 2024: False {True=489,
False=591}
|   |   |   |   |   TransactionDate ≤ Jan 3, 2024: True {True=2,
False=1}
|   |   |   |   TransactionDate ≤ Jan 1, 2024
|   |   |   |   |   PromoValue > 5: False {True=0, False=2}
|   |   |   |   |   PromoValue ≤ 5: True {True=1, False=1}
|   AmountSpent ≤ 5.535: False {True=0, False=4}
```

Table 2. Decision Tree
Accuracy: 66.76%

	true True	true False	class precision
pred. True	21	4	84.00%
pred. False	490	971	66.46%

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class recall	4.11%	99.59%	

Precision: 66.46% (positive class: False)

	true True	true False	class precision
pred. True	21	4	84.00%
pred. False	490	971	66.46%
class recall	4.11%	99.59%	

Recall: 99.59% (positive class: False)

	true True	true False	class precision
pred. True	21	4	84.00%
pred. False	490	971	66.46%
class recall	4.11%	99.59%	

AUC

Figure 2. AUC: 0.705 (positive class: False)

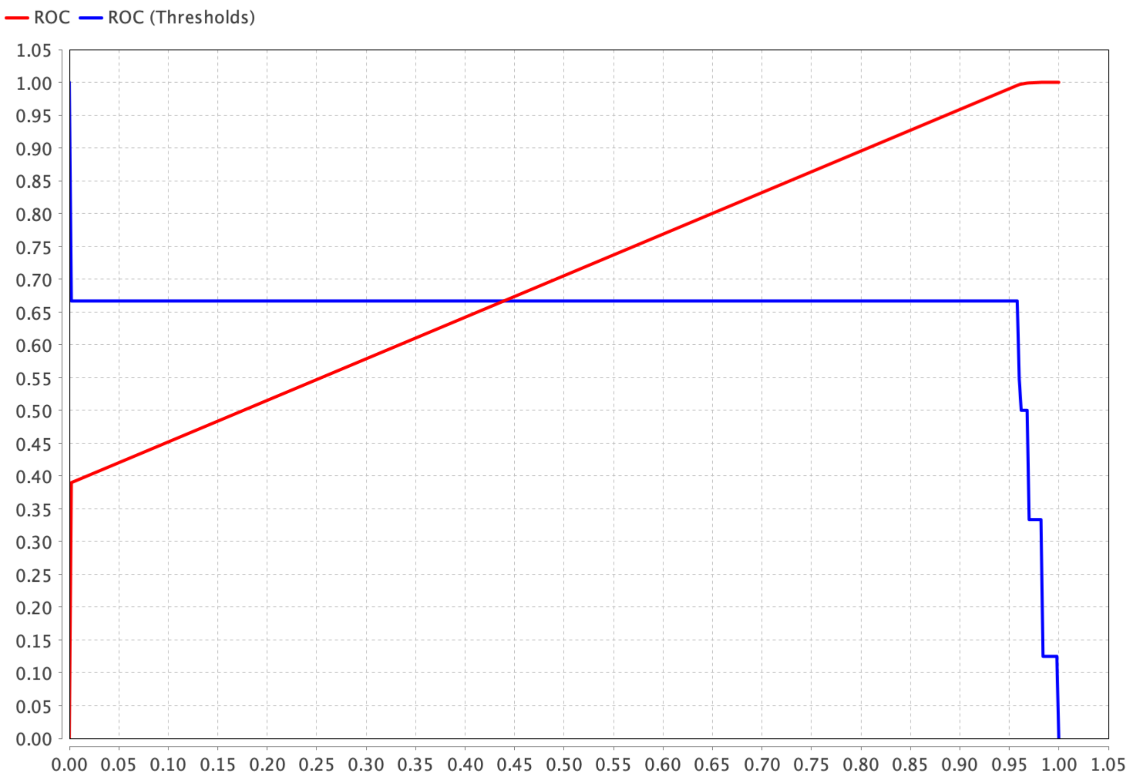

Table 3. KNN

k=1

Accuracy: 100.00%

	true True	true False	class precision
pred. True	511	0	100.00%
pred. False	0	975	100.00%
class recall	100.00%	100.00%	

k=3

Accuracy: 93.67%

	true True	true False	class precision
pred. True	511	94	84.46%

pred. False	0	881	100.00%
class recall	100.00%	90.36%	

k=5
Accuracy: 77.86%

	true True	true False	class precision
pred. True	325	143	69.44%
pred. False	186	832	81.73%
class recall	63.60%	85.33%	

k=7
Accuracy: 74.97%

	true True	true False	class precision
pred. True	283	144	66.28%
pred. False	228	831	78.47%
class recall	55.38%	85.23%	

Table 4. Naïve Bayes
Accuracy: 100.00%

	true True	true False	class precision
pred. True	511	0	100.00%
pred. False	0	975	100.00%
class recall	100.00%	100.00%	

Precision: 100.00% (positive class: False)

	true True	true False	class precision
pred. True	511	0	100.00%
pred. False	0	975	100.00%
class recall	100.00%	100.00%	

Recall: 100.00% (positive class: False)

	true True	true False	class precision
pred. True	511	0	100.00%
pred. False	0	975	100.00%
class recall	100.00%	100.00%	

DISCUSSION

Reducing Churn through Personalized Promo Codes

Findings from the literature review indicate that personalized promo codes, designed based on consumer behavioral data and purchasing history, are more effective in reducing churn compared to generic, mass-distributed promotions. When offers align closely with individual customer preferences, engagement and platform loyalty tend to increase. This highlights the strategic importance of investing in recommendation systems and advanced analytics to tailor promotions more effectively and deliver higher perceived value to targeted user segments.

Risk of Excessive Promo Code Usage

Despite their short-term benefits, the excessive and repetitive use of promo codes may produce unintended consequences. Customers may begin to delay purchases in anticipation of future discounts, eroding long-term brand value and revenue consistency. Additionally, overdependence on promotional incentives may diminish product perception and increase the risk of churn once discounts are withdrawn. Therefore, promo code strategies must be balanced with sustainable value propositions, such as consistent product quality and superior service.

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The Importance of a Positive Customer Experience

While promotional offers play a role in customer retention, they are only part of a larger equation. A holistic customer experience—including fast delivery, responsive customer service, and seamless platform navigation—has a stronger and more sustainable impact on reducing churn. High levels of satisfaction derived from these aspects can foster brand loyalty and mitigate customer migration to competitors. As such, service excellence and operational efficiency must be integrated alongside promotional efforts to maximize customer lifetime value.

Managerial Implications in Managing Promo Code Strategy

From a managerial perspective, e-commerce businesses must adopt a data-driven and customer-centric approach in designing and deploying promo code strategies. Beyond determining the frequency and value of discounts, managers must consider how such promotions align with the overall customer journey. Understanding which customers are most likely to respond to incentives, and identifying optimal timing and channels, is essential to prevent overexposure and reduce dependency. Additionally, promo codes should be incorporated into broader customer retention frameworks, including loyalty programs, service personalization, and post-purchase support, to maintain long-term engagement and reduce churn risk.

Evaluation of Machine Learning Classifier Performance

To support the study's findings, three machine learning classification algorithms—Decision Tree, k-Nearest Neighbor (k=1), and Naïve Bayes—were applied to predict customer churn. The performance of each model is summarized in Table 5.

Table 5. Accuracy Comparison of Machine Learning Algorithms

Algorithm	Accuracy
Decision Tree	66.76%
k-NN (k = 1)	100%
Naïve Bayes	100%

The Decision Tree model achieved moderate accuracy at 66.76%, while both k-NN (k=1) and Naïve Bayes classifiers achieved perfect classification accuracy in this dataset. Although these results appear promising, the exceptionally high accuracy reported for k-NN and Naïve Bayes may be attributed to overfitting or imbalanced class distribution, and should be validated with additional datasets or through cross-validation to ensure generalizability. These preliminary findings underscore the potential of predictive analytics to assist e-commerce platforms in identifying at-risk customers and refining their retention strategies.

CONCLUSION

This study concludes that while promo codes can be an effective tool for reducing customer churn, their impact is highly dependent on how strategically they are implemented. Personalized promo codes—designed based on consumer behavior, preferences, and purchase history—have demonstrated greater effectiveness in enhancing customer engagement and loyalty compared to generic, mass-distributed discounts. However, overreliance on promotional incentives carries the risk of diminishing product value and fostering customer expectations that may lead to churn when discounts are no longer available. Therefore, promo code strategies should be balanced with consistent improvements in product quality, customer service, and overall user experience. A positive and seamless customer journey—encompassing factors such as delivery efficiency, responsive support, and intuitive navigation—plays a crucial role in sustaining customer retention beyond the promotional period. From a managerial standpoint, data-driven decision-making is essential for optimizing promo code deployment. This includes identifying the right customer segments, appropriate timing, and integrating promotions with broader loyalty programs. In addition to relying on promotions, businesses should invest in long-term customer retention strategies such as rewards, personalized communication, and responsive support. Empirical analysis using machine learning further reinforces these conclusions. The results of predictive modeling indicate that the K-Nearest Neighbor (KNN) algorithm with k = 1 and the Naïve Bayes classifier achieved perfect accuracy (100%) in distinguishing between churn and non-churn customers in the dataset, outperforming the Decision Tree model, which yielded lower accuracy (66.76%). These findings suggest that KNN and Naïve Bayes are particularly well-suited for churn prediction when working with structured data and clearly defined features. Consequently, e-commerce platforms can enhance their customer retention strategies by leveraging predictive analytics and integrating promo code campaigns within a broader, customer-centric framework. While the findings offer valuable insights, future studies should consider testing the models on larger, real-world datasets and further exploring the interaction between promotional tactics and user behavior in the Indonesian e-commerce market.

LIMITATION

To clarify the scope and boundaries of this research, several limitations should be acknowledged. First, the scope of the study is confined to Indonesian e-commerce platforms, focusing exclusively on the relationship between promo code usage and customer churn. The findings may not fully represent global market dynamics or other digital commerce ecosystems. Second, this study only examines promo codes offering direct monetary benefits, such as discounts and coupons tied to specific purchases. Other forms of promotional strategies, including cashback programs or bundling offers, are beyond the scope of this analysis.

Third, the research solely investigates the effect of promo codes on customer attrition, without accounting for additional influential factors such as product quality, pricing structure, or macroeconomic conditions. Fourth, the sample and observation period are limited to consumers who actively use promo codes on a single e-commerce platform, with behavioral data collected over a six-month timeframe from January to June 2025. This may constrain the temporal and demographic representativeness of the results.

Fifth, the study applies a quantitative approach through transaction records and surveys, without incorporating in-depth qualitative insights such as customer satisfaction or brand perception. Sixth, several external variables—such as changes in market competition, regulatory shifts, or economic instability—are not analyzed, although they may also influence churn behavior. Finally, the generalizability of findings is limited, as the conclusions are platform-specific and may not be applicable to other types of e-commerce platforms with differing customer segments or operational models.

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