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Research Paper

Enhancing E-Commerce with Big Data: From Browsing to Buying Through Recommendation Systems

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Abstract

This research focuses on analyzing the impact of a recommendation system on customer behavior in the e-commerce industry. This study examines the use of big data-driven product recommendations and tailored promotions to enhance customer engagement, conversion rates, and revenue generation. The importance of prioritizing customer engagement in the early stages of the purchasing process is emphasized, and key statistics related to customer behavior in e-commerce are presented. The objective of this research is to investigate the effectiveness of a recommendation system in influencing customer behavior and driving conversions in the e-commerce industry. The research design incorporates a case study analysis of a prominent marketplace in Indonesia. Data were collected from three automation trigger campaigns: browsing abandonment and purchase reminders. The findings of this research indicate that a recommendation system based on big data has a significant impact on customer behavior in the e-commerce industry. This research highlights the importance of prioritizing customer engagement and implementing effective recommendation systems to drive conversion rates and revenue in the e-commerce industry.

Keywords *Recommendation System, Customer Behavior, E-Commerce, Big Data-Driven*

INTRODUCTION

With the rapid advancement of technology and the exponential growth of the Internet, the world is shifting toward an e-world, where digitalization prevails and accessibility to various services is just a click away (Chao et al., 2022; Xu et al., 2023). E-commerce has witnessed a surge in popularity, becoming the primary medium for commercial transactions through online shopping. Customers are increasingly turning to the internet to purchase various products, and businesses are also embracing online platforms to boost their sales. Prominent e-commerce websites such as Amazon.com and eBay.com have become well established in the market.

In recent years, e-commerce (EC) systems have experienced remarkable growth in sales, driven by technological innovations and improvements in internet-based services (Zhang et al., 2020). This has led to the emergence of numerous large corporations, intensifying competition among them to attract a larger consumer base and achieve higher financial returns. To stay ahead in the competitive landscape, retailers are offering an extensive array of products, attractive deals and discounts, simplified payment processes, and personalized item recommendations based on individual customer preferences (Ji et al., 2022).

Retailers have three main marketing objectives: 1) attracting customers to their stores, 2) encouraging impulse purchases, and 3) influencing the types and quantities of products purchased. These objectives are classified into three categories: attraction effects (decisions regarding store entry or store choice), conversion effects (the percentage of customers making a purchase), and expenditure effects (transaction size and composition) (Guan et al., 2022; Liu et al., 2022). The conversion rate, defined as "the proportion of website visitors who actually place an order" (Chen & Yang, 2023), measures the percentage of site visitors who ultimately make a purchase. It represents a two-step behavior hierarchy that evaluates the rate at which consumers who visit a website convert into purchasers.

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One approach to simplify the shopping experience for customers is to provide them with personalized lists based on their preferences and trends (Supriyanto et al., 2021). These lists are known as recommendation systems. Various studies have proposed effective ways to construct recommendation systems that enhance the efficiency of commercial websites. Recommendation systems (RSs) are information filtering systems that predict consumer ratings or preferences for particular items. RSs play a vital role in helping customers manage large volumes of data (Millar et al., 2018; Urdaneta-Ponte et al., 2021). It increases EC sales by converting website visitors into customers, showcasing new products, enhancing customer loyalty, increasing satisfaction, and encouraging repeat purchases from satisfied customers (Kanwal et al., 2021). Research indicates that personalized RS boosts sales by up to 35% through recommended products (Chaudhary & Chowdhury, 2018; Ebrahimi et al., 2019). Consequently, in the current e-commerce era, the significance of recommendation systems as a key tool for person-to-person marketing is growing continuously (Chaudhary & Chowdhury, 2018).

There are three primary categories of recommendation algorithms: collaborative filtering, content-based filtering, and hybrid recommendation. Collaborative filtering methods rely on collecting and analyzing substantial user behavior, activities, or preference data, and then predicting what users might like based on their similarity to other users (Papadakis et al., 2022; Zhao et al., 2021). The proposed algorithm does not require specialized knowledge, and its recommendation effectiveness improves with user interest. However, it may encounter challenges such as data sparsity (Liang et al., 2018). On the other hand, content-based filtering methods use item descriptions and user preference profiles to recommend items similar to those previously liked by a user (Liang et al., 2018). However, content-based recommendation algorithms have the problem of the diversity of recommended items. Hybrid recommendation systems combine collaborative and content-based filtering, offering potentially more effective solutions in certain scenarios. These methods can address common problems in recommender systems, such as cold start and sparsity issues (Al-Ansi et al., 2018).

However, there is a gap in research on the impact of recommendations based on customer behavior. Previous research has not explored changes in customer browsing patterns based on recommendation levels (Liao et al., 2022). In addition, no studies have investigated the main or interaction effects on website satisfaction (Senecal & Nantel, 2004). Not only that, the effect of other consumer characteristics on the impact of recommendations has not been well studied (Chaudhary & Chowdhury, 2019; Nguyen, 2021). Therefore, the aim of our study was to investigate the impact of a recommendation system that considers tags on purchase decisions and evaluate its ability to predict future purchase behavior. To achieve this goal, we identified the key metrics needed to distinguish between the different categories of browsing abandonment, wishlist/cart leave, and purchase reminders. We will also show the predictive value of these metrics.

Furthermore, we investigate how recommendation systems on e-commerce websites play an important role in providing real-time product recommendations based on past consumer behavior and preferences. These customized recommendations have had a significant impact on increasing customer satisfaction, increasing revenue through incremental and cross-selling, and building long-term relationships between websites and customers. By presenting a comprehensive analysis of the impact of recommendation systems on buying behavior in e-commerce, this research provides valuable insights for industry and academia. The findings from this research will enable businesses to optimize their recommendation strategy, thereby increasing overall consumer engagement and cultivating long-term success in a highly competitive e-commerce environment.

LITERATURE REVIEW

Consumer Behavior in Online Shopping

E-commerce recommendation systems (RSs) facilitate interaction and purchase decisions among users by offering products and services that are not readily available. These systems are influenced by various factors such as demographics, knowledge, and attributes. Various methods have been used to generate personalized purchase recommendations, such as content-based filtering (CF) and demographic-based filtering (DBF). Environmental psychology has been extensively studied to understand how store layouts affect consumer shopping behavior. The stimulus–organism– response (S-O-R) model is used to explore the impact of marketing stimuli on consumer behavior. Shopping orientation is a crucial aspect of shopping behavior models, representing a consumer's general attitude toward shopping. This trait influences store patronage, in-store behavior, and reactions to marketing activities. Nguyen (2021) classified consumers into four types: economic, personalizing, ethical, and apathetic. Wen and Liao (2022) added the recreational shopper, and Shabaz (2019) combined these types into five categories. Each shopping orientation dictates distinct consumer behaviors when selecting a store and during the shopping process. The economic consumer prioritizes low prices and remains unaffected by special displays, whereas the apathetic consumer is disinterested in comparing prices and service levels. The recreational shopper takes time to browse and enjoys the shopping environment, while the personalizing consumer appreciates assistance and information.

The emergence of big data has significantly influenced consumer behavior, affecting external consumption patterns, internal consumption psychology, and other factors. Big data plays different roles in online and offline consumption, particularly in online shopping. With its convenience and variety, online shopping has gained popularity among consumers. The online consumption process generates vast amounts of consumer data, and using this data effectively requires big data-related technologies and tools. By analyzing consumer habits and styles, big data technology can offer personalized marketing and services tailored to each individual.

Businesses can leverage big data analysis to better understand customer preferences, effectively target their audience, and improve overall customer satisfaction. Product recommendations based on big data analysis have been shown to positively impact sales. Personalized experiences driven by big data significantly increase the likelihood of purchase, as consumers are more inclined to purchase when offered individualized experiences. Moreover, customization through big data analysis can boost online sales and cater to the desire for personalized buying experiences. Discounts and promotions based on data analysis have proven effective in converting online and in-store browsers into buyers. By harnessing the power of big data, businesses can optimize their marketing strategies and enhance the online shopping experience for consumers.

While the influence of environmental psychology on consumer behavior in physical stores is well established, and big data has been effectively used in online recommendation systems, there is a research gap in integrating these insights. How can the principles of environmental psychology, which have traditionally been applied to physical retail spaces, be adapted and integrated with big data analytics to enhance the effectiveness of online recommendation systems? This integration could involve translating the stimulus-response models from physical stores to the digital realm, considering how online store layouts, product presentations, and interactive elements impact consumer behavior. Such a study would contribute to the field by bridging the gap between traditional retail psychology and modern big data-driven e-commerce strategies.

Recommendation System for E-Commerce

Recommendation systems assist with user interaction and sales by assisting users in discovering products and services that they may have never discovered on their own. In conventional commerce and business, people are informed about and encouraged to purchase products and services by their acquaintances, the news, and marketers. Due to the increasing use of e-commerce and associated technological developments, the use of RS has become extremely essential due to its benefits. Subscribers, visitors, system administrators, and content are typically provided with products, movies, events, alerts, and articles by recommender systems. Consequently, this method increases conversion rates, customer satisfaction, and loyalty (Nguyen, 2021).

Previous research has proposed various methods in e-commerce recommendation systems (RS) to generate personalized purchase recommendations. One popular method is collaborative filtering (CF), which links users with similar buying patterns, while demographic-based filtering (DBF) matches items to users based on their demographic profile. Knowledge-based filtering (KBF) uses explicit knowledge of item classification, user preferences, and recommendation criteria, whereas content-based filtering (CBF) suggests items that are similar to user attributes. The CF algorithm recommends items that have been enjoyed by users with similar preferences.

There is also research proposing heuristic methods of deep learning-assisted data management (DLHDM) in a topical approach to recommendation systems. This approach introduces a legislative reputation component for trust, performs dynamic analysis of customer behavior, uses statistical methods to support decision making, and implements a recommendation system based on product specifications and similarity measurements (Khatter et al., 2021; Ramshankar & Prathap, 2021). In addition, there are recommendation systems based on fuzzy logic and ontology, as well as the intra- and inter-heterogeneity (ARGO) recommendation model, which integrates various data sources for more accurate recommendations. In total, these studies provide valuable insights and contributions to the development of increasingly sophisticated and effective recommendation systems in the e-commerce world.

While e-commerce group with RS have evolved significantly, incorporating various methodologies such as collaborative filtering (CF), demographic-based filtering (DBF), and knowledge-based filtering (KBF), there appears to be a gap in exploring and implementing certain combinations of these techniques. Specifically, the integration of some of these methods with emerging technologies or novel approaches remains underexplored. For example, combining the precision of CF with the broad spectrum of KBF in conjunction with advanced AI techniques such as deep learning or reinforcement learning could yield more nuanced and effective recommendation systems. In addition, integrating these algorithms with real-time data analytics and adaptive learning models to dynamically adjust recommendations based on ongoing user interactions is an area that has not been extensively researched. Such combinations could lead to breakthroughs in personalization, accuracy, and user engagement in e-commerce recommendation systems. The research could focus on developing and testing these hybrid models, assessing their efficacy compared with traditional singular or more commonly combined approaches, and exploring their impact on user behavior and business outcomes. This exploration of less common algorithmic combinations in RS could open new avenues for innovation in e-commerce technology.

RESEARCH METHOD

Case Selection

ECom B, established in 2011, is one of the prominent marketplaces in Indonesia, capturing attention due to its robust online presence and strategic positioning within the e-commerce landscape. With an employee count ranging from 1001 to 5000 and headquartered in Jakarta, Indonesia, the company has demonstrated its significance within the industry. Operating within the revenue range of $500.0 million to $1.0 billion annually, ECom B has secured a substantial share of the market. The platform's success is attributed to its commitment to customer satisfaction, as evidenced by its operational philosophy "Customer Satisfaction First," which underpins its 24/7 customer service availability and dedication to providing an impeccable shopping experience. ECom B's commitment extends to offering a diverse product range guaranteed to be 100% original, alongside enticing incentives such as free shipping, secure payment options, credit facilities without credit cards, swift delivery, and a flexible 15-day return policy.

ECom B's innovative approach is further exemplified by its adoption of an online-to-offline (O2O) strategy, which combines the online and physical retail realms to enhance customer engagement. This approach is manifested through initiatives such as the ECom B InStore and Click & Collect programs, which allow patrons to seamlessly transition between online and offline shopping modes. Therefore, ECom B seeks to cater to the contemporary omnichannel shopping preferences of its clientele. The company's expansion efforts have encompassed the establishment of fifteen shopping categories, spanning diverse sectors including electronics, fashion, health, and home. By venturing into areas such as mobile and tablets, cameras, computers and laptops, and beyond, ECom B continues to broaden its product offerings to cater to an array of consumer demands.

Experimental Design

Experimental design refers to the process of planning a study to meet specified objectives. It involves making decisions about the conditions under which the data will be collected, the number of experimental units or subjects, and the procedures for data collection and analysis. Experimental design is crucial for ensuring the validity and reliability of the results obtained from an experiment (Maciejewski, 2020; Podsakoff & Podsakoff, 2019). The experiment in the EcommB infrastructure was meticulously designed with a dual objective: first, to integrate and evaluate the behavioral recommendation system using machine learning (BRS-ML) and second, to understand its effectiveness compared to the existing recommendation system. This integration was pivotal for gaining insights into customer interaction and purchase behavior dynamics within the e-commerce platform.

The BRS-ML was seamlessly integrated into the existing EcommB system, functioning in parallel with the legacy recommendation system. The core of this empirical study employed an A/B testing methodology, which was conducted over an extended period from February 28, 2022, to July, 2023. Within this timeframe, customers who interacted with the traditional recommendation system formed the control group, whereas those who received recommendations from the BRS-ML were part of the experimental group. The experiment was specifically designed to analyze three key consumer behaviors in the BMart context: the dynamics of search abandonment, the impact of the Purchase Reminder campaign, and the insights gleaned from combining purchase and click data. This targeted approach was critical in providing a comprehensive understanding of how these specific behaviors affect overall user engagement and conversion rates in the e-commerce environment. Through this focused examination, the study aimed to decode the complexities and subtleties of consumer interactions, thereby offering valuable insights for refining e-commerce strategies, enhancing user experience, and better comprehending the various factors that influence consumer decision-making.

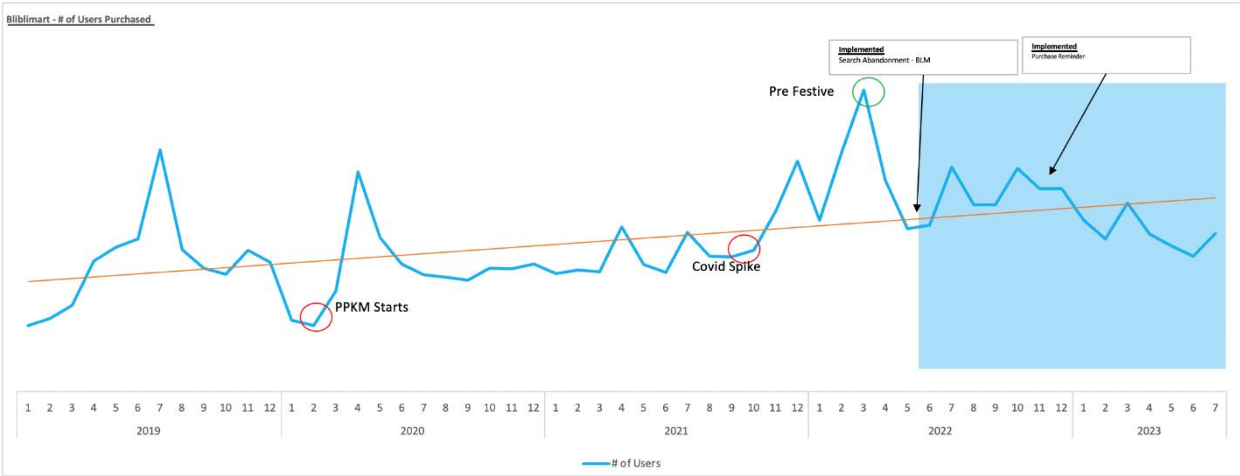

Figure 1. Experimental Timeline

FINDINGS AND DISCUSSION

Findings

The findings provide a comprehensive overview of the dynamic landscape of user engagement and conversion rates within the ECom B platform. Through an intricate architecture driven by behavioral recommendation systems using machine learning (BRS-ML), this analysis unravels the profound impact of personalized recommendations and user behavior insights on customer conversion. From the intricacies of search abandonment patterns to the nuances of purchase reminder campaign performance, the data shed light on the multifaceted factors influencing user interactions, offering invaluable insights for optimizing strategies and enhancing the overall user experience.

System Architecture and Data Flow

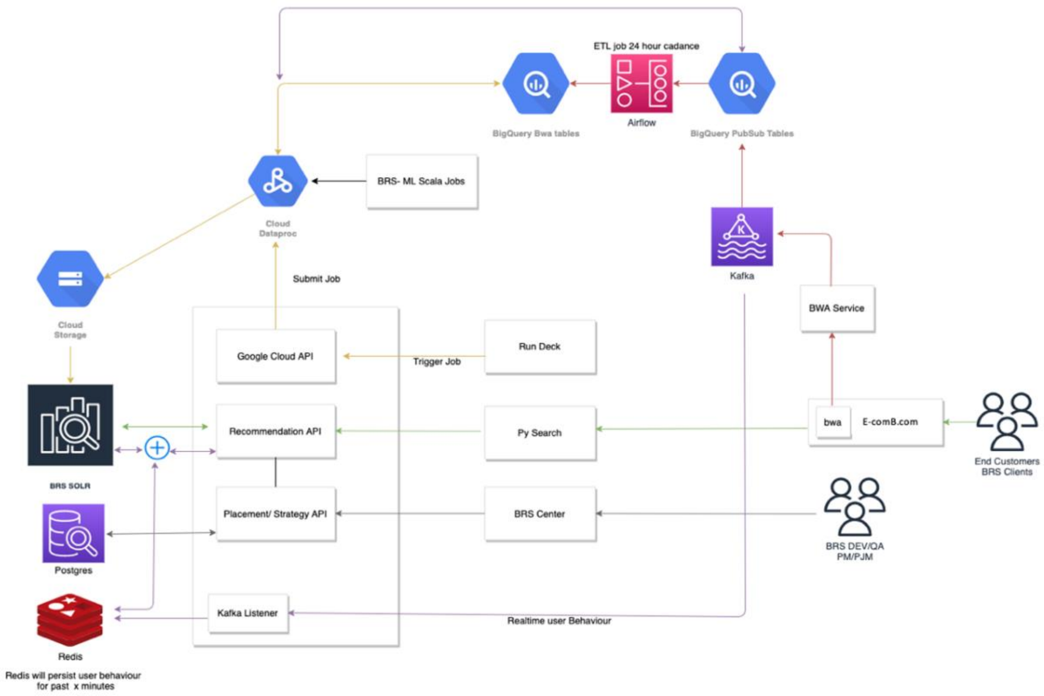

Figure 2. BRS-ML Architecture

The architecture in ECom B has components that are interrelated and function together to generate and present recommendations to users. One of the key components is the Behavioral Recommendation System using Machine Learning (BRS-ML), which leverages user behavior data such as product views, clicks, and add-to-cart stored in BWA BigQuery tables. From this data, BRS-ML generates recommendations tailored to user preferences (Figure 2).

The BRS-API plays an important role in connecting the recommendation results with the users. This API stores recommendations from BRS-ML in brs-solr and serves recommendations to users on the ECom B platform. Brs-solr is the platform used to store and index recommendation data, ensuring fast and efficient data retrieval. Additionally, there is a Google Cloud API that is used to deliver Spark jobs to Google Data Proc, which are scheduled to run in production environments via Rundeck. There is also a Placement/Strategy API that creates placements and associates them with certain strategies, which are later used in the Recommendation API calls.

BWA (BWeb Analytics System) is a user behavior tracking system on a website that utilizes Google Tag manager to collect user events. These data are then processed by the BWA service and sent to Kafka. Kafka is a data streaming platform that retrieves, transmits, and processes data in real time at scale. BigQuery Pub Sub tables are used as data consumers from Kafka, and the data received will be processed and stored via Airflow before being used by BRS-ML.

In the real-time architecture, the BRS-API serves as a consumer of Kafka's BWA events. Events sent by Kafka's BWA are stored in Redis for logged-in and un-logged-in users, with each user's data retained for 30 min. For logged-in users, the member ID (x-auth client member ID) is used, while users who are not logged in are assigned a unique BwaUserId. This BwaUserId is stored on the user's device as a cookie for a long time.

During the recommendation service process, user-specific data such as products viewed, keywords searched, and categories viewed are retrieved from Redis. Existing recommendations for those products and keywords, which are stored in Solr, are then presented to the user. The real-time strategy includes three different approaches:

1. realtimeUserViewHistoryBasedProducts: This strategy recommends similar products on the basis of what the user has seen before. The main strategy used is "contentBased2."
2. Real-timeUserSearchHistoryBasedProducts: Recommendations are based on user search history. The main strategy used here is "addToCartPerSearchTerm."
3. realtimeCategoryAffinity: This strategy uses recently viewed categories as user category affinity. Recommendations on the home page with infinite scrolling are filtered by these categories along with non-real-time category affinity.

This sophisticated architecture exhibits sophisticated recommendation and data processing mechanisms to offer users a personalized and engaging shopping experience on the ECom B platform.

Customer Conversion Journey

Customer Conversion through E-commerce Behavioral Recommender Systems (BRS) and Machine Learning (ML) is a finely woven tapestry that shapes the journey of "NEW MEMBER." This journey was meticulously designed to harness the potential of BRS ML techniques, creating a personalized and optimized experience for both new and existing platform users. The expedition starts with the Welcoming Email Series, in which BRS ML algorithms dissect user behaviors and preferences, tailoring email content for individual resonance and relevance. As users advance to the Welcoming Voucher stage, BRS ML algorithms take center stage in categorizing users based on their behaviors, strategically allocating vouchers that align with their purchase inclinations. For those transitioning into the "EXISTING MEMBER" cohort, the influence of BRS ML is sustained through the Email New Member Conversion phase. The dynamic personalization of these emails, driven by real-time behavioral insights, augments conversion prospects by aligning recommendations with each user's unique preferences. Additionally, the infusion of BRS ML into the referral code mechanism enhances the effectiveness of the member-get-member program. By scrutinizing the behavioral nuances of both referrers and referred users, BRS ML can suggest optimal pairs, fostering mutual benefit and elevating program success.

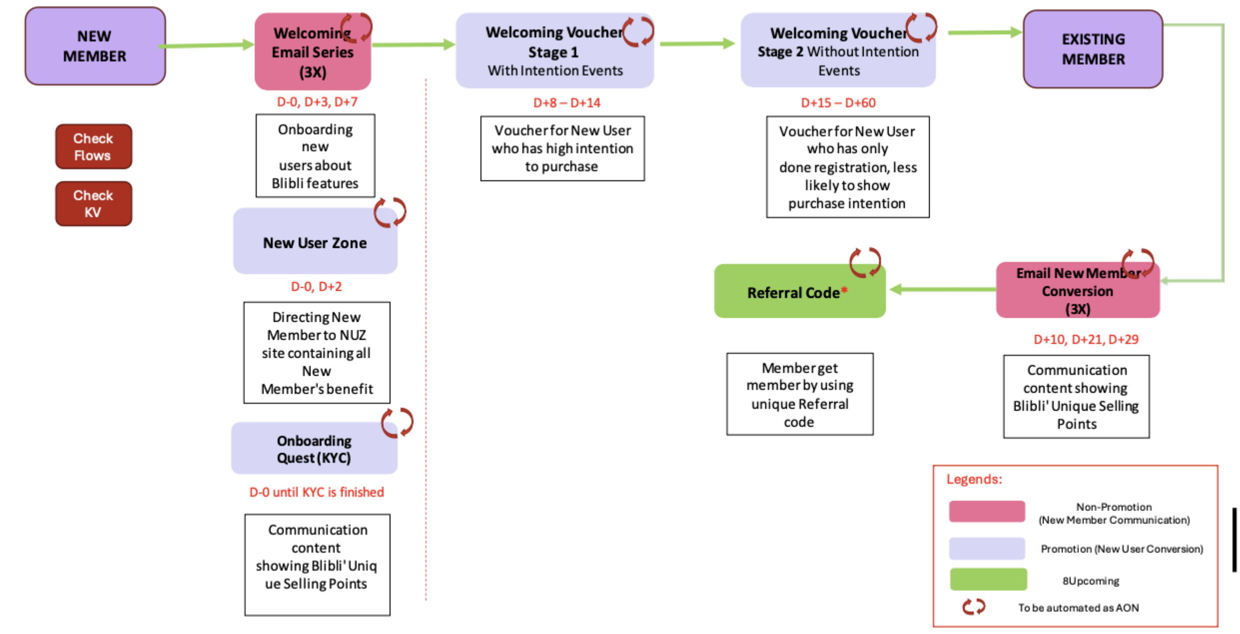

Figure 3. Costumer Conversion on EComm B

Search Abandonment

The presented data illustrate the progression of search abandonment over time. In 2022, the number of impressions fluctuated, with a peak of 191,400 in June and a low of 31,260 in May (Figure 4). Throughout the months, the number of visits and converted users fluctuated correspondingly. Notably, there were 250,770 views and 54,640 conversions in June, indicating a higher engagement rate than in other months. This observation indicates that June exhibited an exceptionally high level of user engagement and conversion. In the subsequent months of 2022, impressions, views, and conversions also fluctuated. This variation highlights the intricate relationship between user engagement and conversion rates, highlighting the need for a deeper investigation into the fundamental causes of these fluctuations.

The data indicate that this fluctuating pattern in impressions, views, and converted users will continue into 2023. In March 2023, for instance, there were 135,440 impressions, 130,310 views, and 29,900 conversions. While the number of impressions and interactions remained relatively high, the conversion rate was significantly lower in March, indicating a trend of decreased engagement and conversion.

Intriguingly, as the data advances to July 2023, a significant development emerges. Even though impressions and interactions decreased, the number of converted users increased to 14,850. Despite a decrease in engagement, this scenario suggests a higher conversion rate, suggesting that July's strategies or contextual factors contributed to more effective conversions (Table 1).

These findings highlight the dynamic nature of search abandonment, which is influenced by seasonality, market trends, and consumer behavior. The sharp increase in June and July 2022, which occurred during the period before the fasting month in some cultures, was followed by a decrease in early 2023, when the fasting month was observed, demonstrating the impact of seasonality and marketing campaigns on user engagement. The complex relationship between impressions, clicks, and conversions is reflected in the interplay between impressions, clicks, and conversions. Detailed analysis of these patterns can provide businesses with valuable insights for optimizing their strategies, enhancing the user experience, and proactively addressing the issues associated with search abandonment. This data-driven strategy can facilitate improved decision-making and ultimately improve user engagement and conversion rates.

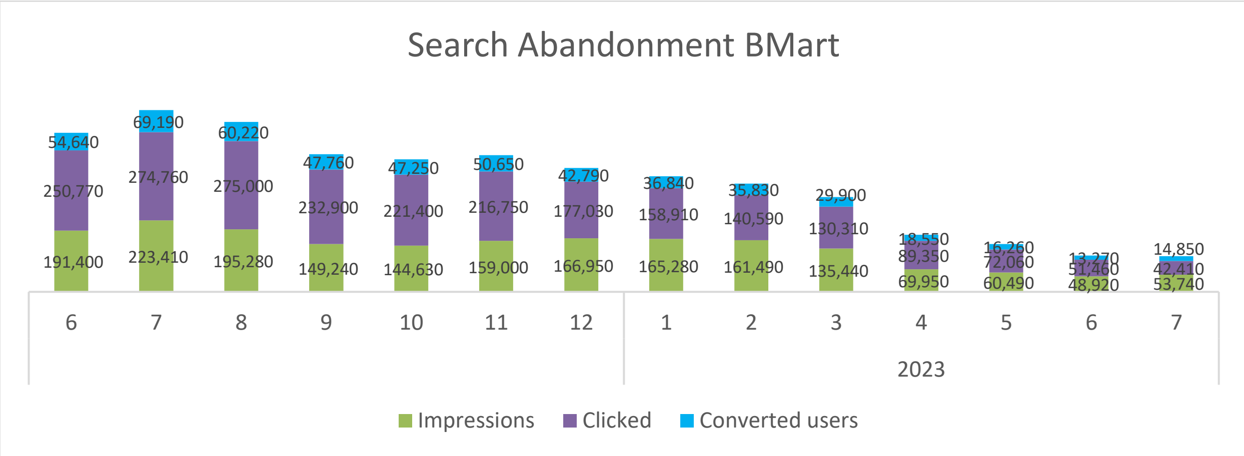

Figure 4. Search Abandonment BMart (Source: Author)

Table 1. Statistics of the Search Abandonment BMart

	Impressions	Clicked	Converted Users
Average	134,365.92	150,696.23	37,966.53
Standard Deviation	67,793.04	81,881.92	19,688.25
Minimum	48,920.00	42,410.00	13,270.00
Maximum	223,410.00	275,000.00	69,190.00

Purchase Reminder

The provided data describes the performance of a purchase reminder campaign over time (Figure 5). In June 2022, the journey of the campaign began with 9,877 impressions, 1,242 interactions, and 754 converted users. In subsequent months, particularly July and August, impressions, interactions, and conversions increased significantly. In July, 47,540 impressions, 17,336 clicks, and 2,778 users converted, followed by 56,224 impressions, 22,636 clicks, and 3,017 users who converted in August.

There were monthly fluctuations in impressions, interactions, and converted users as the campaign progressed. These fluctuations illustrate the campaign's fluctuating levels of engagement and conversion rates. In some months, such as October and November, the number of impressions and clicks remained comparatively high, but the corresponding conversion rates fluctuated (Table 2). The data indicate a continuing trend of variations in campaign performance through 2023. In March 2023, for instance, there were 37,663 impressions, 25,175 views, and 1,062 conversions. In July, the final month of the campaign, 18,289 impressions, 10,756 interactions, and 723 converted users were recorded.

These data highlight the dynamic nature of purchase reminder campaigns and the complexities of promoting user engagement and conversions. Numerous factors, including seasonal trends, consumer behavior, and the overall market context, influence the success of the campaign. Pattern analysis of this data can provide valuable insights for optimizing future purchase reminder campaigns, boosting user engagement, and ultimately increasing conversion rates. In terms of user interactions and campaign performance, strategic decisions can be influenced by a thorough analysis of these metrics.

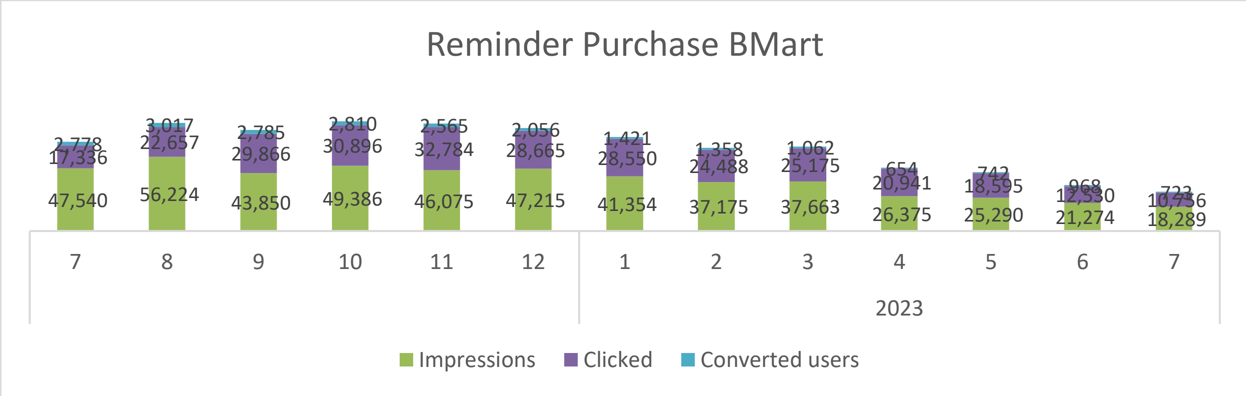

Figure 5. Reminder to purchase BMart (Source: Authors)

Table 2. Statistics of reminder purchase BMart

	Impressions	Clicked	Converted Users
Average	35,903.54	21,198.54	1,948.92
Standard Deviation	35,903.54	8,781.39	1,005.74
Minimum	18,289	10,756	654
Maximum	56,224	32,784	3,017

Combining purchase and click data

The presented data sheds light on user purchasing behavior, offering a distinction between those who engaged in customer relationship management (CRM) assistance and those who did not. Examining the data further, in May 2022, a total of 163,528 users completed purchases, with 156,218 of them proceeding without using CRM support. The subsequent month, June, saw 166,834 users making purchases, of which 111,440 chose non-CRM transactions. As the months progressed, distinct patterns emerged. Notably, in July, 166,834 users made purchases, and 111,440 opted for non-CRM transactions. This interplay of data highlights the potential influence of CRM assistance on user purchasing decisions, suggesting a dynamic relationship that could be further explored through analytical tools such as the Behavioral Recommender System using Machine Learning (BRS-ML). This system, known for its ability to analyze user behavior and preferences, could provide deeper insights into the observed patterns and potentially offer strategies to optimize user engagement and transactions within both CRM-assisted and non-CRM scenarios.

Moving forward, July revealed an increase in engagement, with 225,462 users making purchases, of which 153,494 chose not to use CRM (Figure 6). This pattern of divergent user behavior persisted in August, when 187,315 users made purchases and 124,078 did so without using CRM. This pattern persisted throughout subsequent months, revealing variations in the number of users who adopted CRM assistance for their purchases.

The trend continued into 2023, as 171,798 users made purchases in January, while 133,537 did so without CRM support. Similarly, 153,020 users made purchases in February, with 115,832 opting for non-CRM transactions. These patterns persisted as the data progressed through March, April, and beyond, indicating a consistent trend of users using or not using CRM assistance for their purchasing decisions.

This dataset highlights the dynamic relationship between CRM usage and user purchasing behavior. The numbers illustrate the potential impact of CRM strategies on user engagement and conversion rates. Analyzing these patterns can provide valuable insights into the efficacy of CRM implementations, enabling businesses to better accommodate user preferences and enhance the overall user experience. The exhaustive evaluation of these metrics aides in comprehending the impact of CRM in fostering user engagement and facilitating successful transactions.

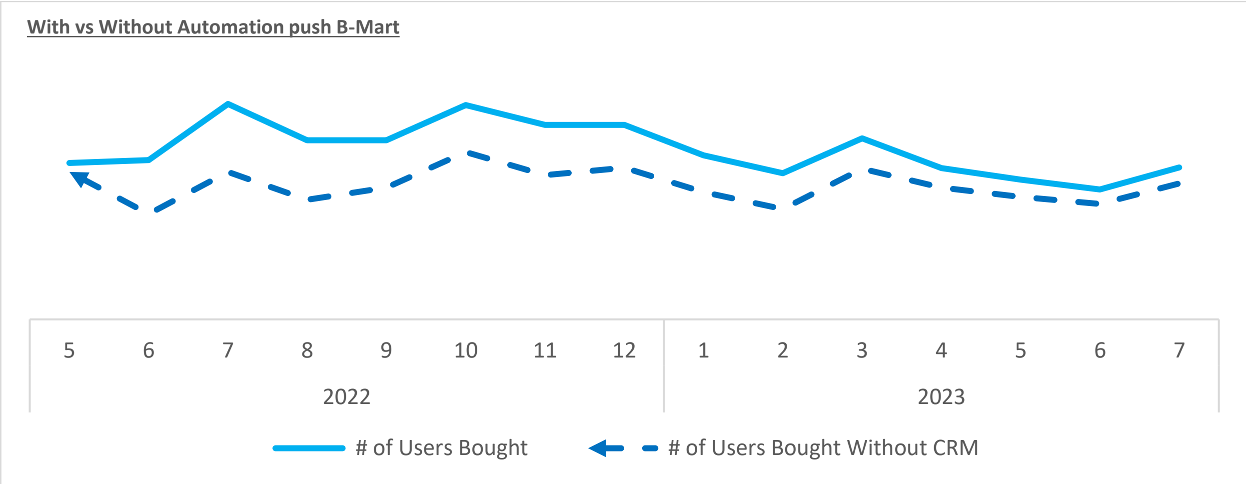

Figure 6. Differentiation of Users Bought with or without CRM

Table 3. Statistics of Users Bought with and Without CRM

	Users Bought using CRM	Users Bought Without a CRM
Average	186.074	137.478
Standard Deviation	26.071	17.636
Minimum	135.934	111.440
Maximum	225.462	174.192

The results of data analysis show that users who buy using customer relationship management (CRM) experienced a significant increase in the study period. From May 2022 to July 2023, an increasing number of users made successful CRM-assisted purchases. This increase reached around 33.09% when compared with users who made purchases without using CRM. The calculated t-statistic of -13.26 and an extremely low p-value of approximately 2.65×10^{-13} confirm the statistical significance of this difference (Table 3).

Discussion

The analysis of user behavior and conversion rates in this study delves deep into the realm of recommendation systems and their influence on user actions and purchase decisions. By examining click-through rate (CTR) and conversion rate (CVR), this study provides valuable insights into how customer relationship management (CRM) assistance impacts user engagement and subsequent conversion behavior. This analysis builds upon prior research that explored the effects of recommendation systems on user actions. The integration of the Behavioral Recommender System using Machine Learning (BRS-ML) resonates with Alagarsamy et al. (2023), emphasizing the importance of advanced recommendation algorithms for enhancing user engagement. The substantial 33.09% increase in purchase transactions underscores the potential of hybrid recommendation architectures in driving conversions, aligning with Hussien et al. (2021), who focused on improving recommendation accuracy for better outcomes.

The synthesis of the cited research studies highlights the central role that recommendation systems play in influencing consumer behavior and decision-making within the e-commerce industry. These studies elucidate the manner in which online product recommendation systems exert influence over the consumer decision-making process, the duration of consumer engagement on e-commerce platforms, and the cultivation of customer loyalty (Nadeem et al., 2015). By design, these systems intricately analyze consumer behavior patterns and preferences, culminating in the provision of bespoke product recommendations (Bohra & Bartere, 2022). These recommendations are borne out of a deep learning process that imbibes insights from previous consumer comments and reviews, thereby aiding customers in unearthing novel products and navigating purchase decisions (Alabdulrahman et al., 2020). These investigations also underscore the contemporary focus on personalized recommendation paradigms founded on consumer behavior and propelled by intelligent algorithms, culminating in an augmented decision-making trajectory (Hussien et al., 2021). The proposition of a consumer-centric multi-party matching recommendation system, rooted in deep learning and attuned to individual consumer attributes, further emphasizes the indispensability of a nuanced understanding of consumer characteristics. Moreover, the innovation of a consumer recommendation methodology based on facial recognition user profiles and historical shopping data evokes novel prospects for comprehending consumer behavior beyond the confines of traditional online actions (dos Santos et al., 2021).

The study's approach of introducing the "Search Abandonment" and "Purchase Reminder" campaigns, highlight the significance of personalized recommendations. The observed differences in impressions, CTR, and conversion rate (CVR) between the two campaigns reinforce the need to evaluate multiple metrics when assessing recommendation system effectiveness. This insight connects with Liu's (2022) advocacy for comprehensive evaluation strategies that consider both engagement and conversion metrics. Furthermore, the study's emphasis on not solely relying on CTR but considering CVR as a key success measure aligns with Liu et al. (2022) explored multifaceted approaches to evaluate recommendation systems' performance.

The study's contribution extends beyond its specific findings and methodologies. It aligns with previous research on recommendation systems and user behavior analysis by acknowledging the importance of adaptable and comprehensive systems. The adoption of a hybrid recommendation system echoes research that has stressed the limitations of conventional approaches and the need for innovative strategies (Badriyah et al., 2020). Moreover, the integration of expert systems, exemplified by the (Custom Expert Recommendation System (CERS), showcases the synergy between machine learning techniques and expert knowledge to enhance recommendation accuracy. This integration resonates with studies that have explored customization and expert-driven approaches to refine recommendation systems (Agarwal et al., 2022).

The exploration of CRM assistance's impact on user behavior and conversion rates resonates with the ongoing discourse on recommendation system usage dynamics. By focusing on the differentiation between CRM-assisted and non-assisted transactions, this study contributes to understanding the adaptability of recommendation systems to diverse user behaviors (Dubey &

Sangle, 2019). This aligns with prior research trends that underscore the importance of personalization and responsiveness to user preferences.

This study's analysis and findings seamlessly integrate with prior research in recommendation systems and user behavior analysis. By addressing limitations, exploring innovative techniques, and delving into user engagement and conversion dynamics, this study advances the understanding of how recommendation systems can optimize user experiences and drive conversions. As the landscape of recommendation strategies continues to evolve, the insights gained from this study offer valuable guidance for refining strategies and designing systems that cater to users' preferences and behaviors.

CONCLUSIONS

The study within the ECom B framework significantly advanced the understanding of e-commerce customer conversion by effectively leveraging the behavioral recommendation system using machine learning (BRS-ML). This was achieved through focused campaigns like "Search Abandonment" and "Purchase Reminder," which were instrumental in comparing the effectiveness of BRS-ML with conventional recommendation systems. Through meticulous A/B testing, the study scrutinized customer interactions, uncovering how BRS-ML recommendations influenced click-through rates and actual product purchases. This analysis not only confirmed the superior performance of BRS-ML but also revealed complex dynamics between substitute and complementary product suggestions, providing deep insights into customer interaction and transaction patterns.

The "Search Abandonment" campaign highlighted the fluctuating nature of engagement and conversion rates, emphasizing the intricate interplay between impressions, clicks, and conversions and the need for nuanced e-commerce strategies. Similarly, the "Purchase Reminder" campaign's varied performance over time sheds light on the multifaceted aspects of user engagement and conversion in e-commerce. Furthermore, by combining purchase and click data, the study showcased the significant impact of customer relationship management (CRM) strategies on user purchasing behavior, offering insights for optimizing CRM approaches.

The conclusive impact analysis quantified the success of the implemented strategies, notably demonstrating a 33.09% increase in post-push order placements. This substantial improvement underscores the effectiveness of the "Search Abandonment" and "Purchase Reminder" strategies, highlighting their role in not only influencing user behavior but also boosting user engagement and transaction rates. These results provide valuable implications for enhancing e-commerce practices, benefiting both industry practices and academic research. The study's comprehensive approach and data-driven insights validate the efficacy of BRS-ML and open new avenues for future research and application in the e-commerce sector.

Research Implications

This study contributes to the academic comprehension of customer behavior in the e-commerce environment. The investigation of complex relationships between substitute and complementary product recommendations sheds light on the influence of recommendation systems on consumer decisions. The inconsistent performance of the "Search Abandonment and Purchase Reminder" campaigns highlights the complexity of user engagement and conversion, providing fertile ground for future research into the multifaceted nature of consumer interactions in e-commerce environments. In addition, the study's examination of the effect of customer relationship management (CRM) assistance on user purchasing behavior offers a novel perspective on the optimization of CRM strategies. This suggests a possible direction for future research that investigates the interaction between CRM strategies and customer decision-making processes in greater depth. The data-driven methodology and meticulous A/B testing methodology presented here provide a foundation for other researchers to conduct similar studies or extend the analysis to investigate additional factors influencing user behavior and conversion in e-commerce environments.

LIMITATION AND FURTHER RESEARCH

While this study assesses recommendation system effectiveness using metrics such as click-through rates and conversion rates, there is a need for a more comprehensive understanding through an in-depth analysis of the quality of user engagement, considering factors such as browsing depth, time spent on pages, and interaction patterns. Additionally, expanding the analysis to encompass cross-platform comparisons would provide broader insights into recommendation system performance across diverse e-commerce platforms and contexts. Exploring the long-term impacts of recommendation strategies through a longitudinal analysis could shed light on their sustained efficacy over time. Finally, as the e-commerce landscape evolves, exploring dynamic recommendation approaches that adapt in real time to changing user preferences and market trends could enhance the agility and responsiveness of recommendation systems. Addressing these aspects and pursuing the suggested research directions would significantly contribute to enhancing our understanding of the role of recommendation systems in shaping user behavior, enriching customer engagement, and optimizing conversion rates in the dynamic domain of e-commerce.

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