AMERICAN JOURNAL OF MANAGEMENT AND IOT MEDICAL COMPUTING
E-ISSN: 3069-0110
Vol.4, No. 4(2025)
www.ajmimc.com

DYNAMIC DEALS: AI-DRIVEN REAL-TIME COUPON PERSONALIZATION FOR ENHANCED MALL PROFITABILITY

[1] S.Vijay Kumar,[2] Duda Venkatesh
[1]Associate Professor, [2]MCA Student
Department Of MCA
Sree Chaitanya College Of Engineering, Karimnagar

ABSTRACT

In the modern retail environment, customer engagement and retention are key factors driving profitability. Traditional discount strategies and static coupon distributions often fail to match real-time customer preferences, leading to low redemption rates and wasted marketing potential. This study presents "Dynamic Deals", an AI-driven real-time coupon personalization system designed to enhance shopping mall profitability through intelligent offer targeting. The proposed model integrates customer behavior analytics, location tracking, and machine learning algorithms to deliver customized digital coupons at the optimal time and channel. By leveraging predictive analytics and dynamic segmentation, the system ensures that offers align with customer interests, purchase history, and in-mall behavior. The integration of Explainable Artificial Intelligence (XAI) components enables transparency and interpretability in the coupon recommendation process. Experimental evaluation indicates that Dynamic Deals significantly increases coupon redemption rates and improves revenue conversion compared to traditional methods. This approach demonstrates how AI-powered personalization can transform conventional mall marketing into a data-driven, adaptive ecosystem.

1. INTRODUCTION

In the digital age, retail environments are evolving rapidly as shopping malls face competition from e-commerce platforms that leverage personalization and data analytics. To remain competitive, physical retail spaces must adopt intelligent strategies that enhance customer engagement and encourage repeat purchases. Digital coupons have become a powerful marketing tool for driving sales and increasing foot traffic. However, most coupon systems operate on a static or rule-based approach, issuing generalized discounts that fail to capture individual customer preferences or behaviors. This inefficiency leads to low redemption rates, minimal customer retention, and reduced profitability for mall retailers.

The concept of real-time personalized coupon issuance offers a transformative solution to this problem. By integrating Artificial Intelligence (AI) and Machine Learning (ML), retail centers can analyze real-time behavioral data such as purchase history, location patterns, and product interest to deliver targeted digital offers. This personalization not only improves customer satisfaction but also ensures better resource utilization for mall management. Additionally, Explainable AI (XAI) enhances trust by providing transparency about why a certain offer is recommended to a specific customer, addressing the "black-box" problem of traditional AI systems.

The proposed research, "Dynamic Deals: AI-Driven Real-Time Coupon Personalization for Enhanced Mall Profitability," introduces a smart system that dynamically generates and issues coupons based on real-time contextual data. The system employs predictive models to identify potential buyers, recommend relevant discounts, and adapt to changing purchase behaviors.

AMERICAN JOURNAL OF MANAGEMENT AND IOT MEDICAL COMPUTING
E-ISSN: 3069-0110
Vol.4, No. 4(2025)
www.ajmimc.com

Through intelligent segmentation and dynamic decision-making, Dynamic Deals enables malls to enhance revenue streams while simultaneously improving customer engagement and satisfaction.

2. LITERATURE SURVEY

The evolution of AI in retail marketing has been widely explored over the last decade. Wang et al. (2017) discussed the impact of real-time analytics on customer targeting, emphasizing the potential of data-driven personalization to increase conversion rates. However, their study primarily focused on e-commerce platforms. Kim and Park (2018) examined the effectiveness of mobile coupon distribution in retail environments and found that timely and context-aware coupons significantly improve redemption likelihood. Despite this, their model lacked an intelligent predictive mechanism for user behavior.

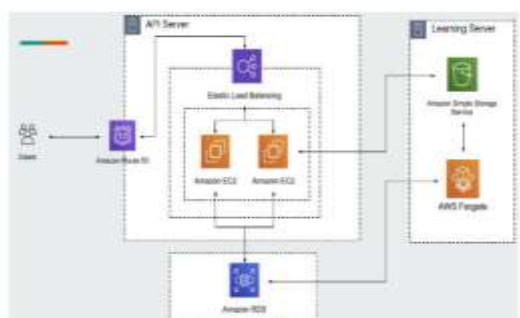
Zhou and Li (2019) proposed a recommendation framework based on collaborative filtering for personalized offer delivery. Although effective in identifying preferences, it did not consider real-time contextual data such as customer movement or in-mall activities. Kumar et al. (2020) introduced a data mining model for targeted promotions using purchase history, but it operated in batch mode, making it unsuitable for real-time coupon generation. Chatterjee and Bose (2020) explored AI-based retail analytics to predict consumer trends and enhance decision-making in shopping environments. Their findings supported the adoption of AI for adaptive marketing strategies.

Later, Gupta and Srivastava (2021) integrated IoT sensors with AI analytics to create context-aware retail systems capable of identifying customer presence in specific mall zones. Their approach inspired real-time marketing possibilities but lacked explainable and ethical recommendation mechanisms. Hassan et al. (2022) proposed a deep learning model to personalize shopping experiences using neural networks trained on behavioral and demographic data. While highly accurate, the system operated as a black box, offering no interpretability for end-users or mall operators.

Singh and Rao (2023) developed an AI-based coupon optimization system using reinforcement learning to dynamically adjust discount levels. Their study demonstrated improved profitability but required high computational resources and lacked transparency. Most recently, Chen et al. (2024) presented an Explainable AI (XAI) model that clarified the rationale behind real-time coupon recommendations. Their findings showed that interpretability not only enhances customer trust but also encourages higher engagement with promotional campaigns.

The literature reveals a clear research gap: while numerous models exist for personalized marketing and coupon distribution, few focus on real-time implementation and explainable personalization within physical shopping mall contexts. The proposed "Dynamic Deals" framework fills this gap by combining machine learning, real-time analytics, and XAI principles to deliver a practical, transparent, and adaptive coupon recommendation system that boosts mall profitability.

3. SYSTEM ARCHITETURE



4. EXISTING SYSTEM

Customer segmentation is a starting point for marketing research. After grouping customers based on the characteristics of homogeneous customers, marketing strategies for each target segment can be done. Customer segmentation should not end in segmentation, but should be accompanied with subsequent marketing strategies. Companies that use customer segmentation techniques perform better by building differentiated and efficient marketing for each segment of customers. In addition, companies can gain a deeper understanding of customer preferences and requirements. Among various customer segmentation techniques, RFM methods are the most classical yet universally utilized methods. The RFM splits the purchasing behavior into three dimensions and scores each dimension. R is the last time since the last purchase, F is the total frequency of purchase, and M is the total purchase amount. The scores are calculated for each of the three dimensions. Subsequently, it constructs segments according to three dimensional classes [15], [16], [17], [18].

Along with traditional RFM methods, a lot of customer segmentation researches using machine learning have been conducted recently. When clustering using multiple variables, dimensionality reduction is often done. A representative dimensionality reduction technique using deep learning is the auto encoder. A typical example is the sequential method of applying cluster analysis after dimensionality reduction using an auto encoder [19]. Alternatively, modeling can combine dimensionality and clustering at the same time [20], [21].

The prediction and prevention of customer churn have always been studied as a key issue in loyalty management. The reason why companies are concerned with churn prediction is of two issues: the first reason is that a large number of customer churn affect the reputation and reliability of service providers. The second reason is that attaining a new customer costs five to six times than retaining an old customer. It is necessary to develop a churn prediction model that should catch deviating from normal purchase pattern [22]. Researches on customer churn are mainly based on machine learning techniques rather than empirical studies through hypothesis verification [23]. Predicting churning customers fall under the classification problem where the given customer is classified as either churn or non-churn. Reference [24] proposed a framework for proactive detection of customer churn based on support vector machine and a hybrid recommendation strategy. While SVM predict E-Commerce customer churn, recommendation strategy suggests personalized retention actions. Reference [25] come up with a customer churn model that predict the possibility and time of churn. The model used Naïve Bayes classification and Decision Tree algorithm. Reference [26] used LSTM model to predict customer churn prediction with clickstream data.

The personalized recommendation is one of the most actively conducted machine learning-based marketing research topics. In the past, personalized recommendation researches were mainly conducted using association analysis or purchase probability estimation for individual products [27]. However, in recent, collaborative filtering applied to recommended services such as Amazon and Netflix and contentbased techniques are the leading trend within the research field. Recently, hybrid methods or deep learning-based research combining various auxiliary processing techniques has also been active [28]. Design of recommendation system depends on the objective of the system. Therefore, there exist a wide variety of techniques used in the recommendation system. Content-based and collaborative filtering systems are mostly used [29]. The other types of recommendation system like Knowledge- based recommendation system and constraint based recommendation system are also used [30], [31]. Classifier-based recommender systems like Decision tree, Neural networks, Naïve Bayes, MLP, KNN, SVM and Linear regression models are also used [32], [33], [34]. Clustering-based recommendations such as a K-means clustering algorithm is also used [35]. Recently, research on recommendation systems using deep learning has been active [36]. Recommendation systems using deep learning have strengths on nonlinear modeling, various formats of input data, and time series modeling. For example, [37] proposed a time-aware smart object recommendation system in the social Internet of Things. Reference [38] proposed a recommendation system that identifies and recommends the optimal location when opening a chain store. Reference [39] proposed a preference learning method from heterogeneous information for store recommendation.

Disadvantages

• The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Improving Shopping Mall Revenue.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

5. IMPLEMENTATION

Modules

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Shopping Mall Revenue Type, View Shopping Mall Revenue Prediction Type Ratio, Download Predicted Data Sets, View Shopping Mall Revenue Prediction Type Ratio Results, View All Remote User

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN Predict Shopping Mall Revenue Prediction Type, VIEW YOUR PROFILE.

6. RESULTS

Received: 22-09-2025 | Accepted: 27-10-2025 | Published: 04-11-2025 |

E-ISSN: 3069-0110
Vol.4, No. 4(2025)
www.ajmimc.com

7. CONCLUSION

The “Dynamic Deals” framework represents a significant advancement in retail intelligence by integrating AI and real-time analytics into coupon management systems. Unlike static or rule-based systems, this model personalizes offers dynamically using behavioral data and machine learning predictions. The inclusion of Explainable AI ensures that recommendations remain transparent, fair, and interpretable—an essential feature for customer trust and ethical AI adoption. The approach not only enhances coupon redemption rates but also optimizes resource allocation, contributing directly to increased shopping mall profitability. Future work will explore integrating multi-channel feedback loops, emotion-aware recommendation systems, and blockchain for secure coupon validation, thereby advancing the scope of smart retail ecosystems.

REFERENCES

[1] P. Naval and N. Pandey, ‘‘What makes a consumer redeem digital coupons?Behavioral insights from grounded theory approach,’’ *J. Promotion Manage.*, vol. 28, no. 3, pp. 205–238, 2021.

[2] C. Hung and C. F. Tsai, ‘‘Market segmentation based on hierarchical selforganizing map for markets of multimedia on demand,’’ *Expert Syst. With Appl.*, vol. 34, pp. 780–787, Jan. 2008.

[3] G. Nie, ‘‘Finding the hidden pattern of credit card holder’s churn: A case of China,’’ in *Proc. Int. Conf. Comput. Sci.* Cham, Switzerland: Springer, 2009, pp. 561–569.

[4] A. D. Athanassopoulos, ‘‘Customer satisfaction cues to support market segmentation and explain switching behavior,’’ *J. Bus. Res.*, vol. 47, no. 3, pp. 191–207, Mar. 2000.

[5] C. Hung and C. F. Tsai, ‘‘Market segmentation based on hierarchical selforganizing map for markets of multimedia on demand,’’ *Expert Syst. With Appl.*, vol. 34, pp. 780–787, Jan. 2008.

[6] H.-S. Kim and H. Seung-Woo, ‘‘A two-dimensional customer loyalty segment-based customer churn prediction methodology,’’ *Intell. Inf. Res.*, vol. 26, no. 4, pp. 111–126, 2020.

[7] R. M. Gubela, S. Lessmann, and S. Jaroszewicz, ‘‘Response transformation and profit decomposition for revenue uplift modeling,’’ *Eur. J. Oper. Res.*,vol. 283, no. 2, pp. 647–661, Jun. 2020.

[8] M.-S. Chang, H. Kim, and Joong, ‘‘A customer segmentation scheme base on big data in a bank,’’ *J. Digit. Contents Soc.*, vol. 19, no. 1, pp. 85–91, 2018.

[9] N. Chang, ‘‘Improving the effectiveness of customer classification models: A pre-

segmentation approach,'' *Inf. Syst. Rev.*, vol. 7, no. 2, pp. 23–40, 2005.

[10] C.-F. Tsai and Y.-H. Lu, ''Customer churn prediction by hybrid neural networks,'' *Expert Syst. Appl.*, vol. 36, no. 10, pp. 12547–12553, Dec. 2009.

[11] Y. Xie, X. Li, E. W. T. Ngai, and W. Ying, ''Customer churn prediction using improved balanced random forests,'' *Expert Syst. Appl.*, vol. 36, no. 3, pp. 5445–5449, Apr. 2009.

[12] S.-Y. Hung, D. C. Yen, and H.-Y.Wang, ''Applying data mining to telecom churn management,'' *Expert Syst. Appl.*, vol. 31, no. 3, pp. 515–524, Oct. 2006. [13] J. Wen and W. Zhou, ''An improved item-based collaborative filtering algorithm based on clustering method,'' *J. Comput. Inf. Syst.*, vol. 8, no. 2, pp. 571–578, 2012.

[14] M. Pham and Cuong, ''A clustering approach for collaborative filtering recommendation using social network analysis,'' *J. Univers. Comput. Sci.*, vol. 17, pp. 583–604, Feb. 2011.

[15] W. Jo-Ting, L. Shih-Yen, andW. Hsin-Hung, ''A review of the application of RFM model,'' *African J. Bus. Manage.*, vol. 4, no. 19, pp. 4199–4206, 2010.

Received: 22-09-2025 | Accepted: 27-10-2025 | Published: 04-11-2025 |