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# Improving Shopping Mall Revenue by Real Customized Digital Coupon Issuance

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**ABSTRACT:** With big data & deep learning technology becoming more popular, they've to enter the marketing world too. Marketing is a key part of business administration. One really important area in marketing is managing customer churn—basically, stopping customers from leaving. In this paper, we suggest a cool way to help keep customers around and boost sales. We do this by sending out special discount coupons to customers who might leave, all in real time big data.

First, we looked at different customer groups through two-dimensional analysis. Then, we created a real-time model that estimates how likely each group is to churn, by using their clickstream data. After that step, we sent out those customized coupons to our clients. In the end, we saw how well these efforts worked by checking the conversion rates and sales growth.

Guess what? Our method, which combined two-dimensional cluster analysis with a recommendation system, turned out to be way better than simpler models on their own. By using this new model, online shopping malls can boost sales without having to spend too much on marketing—oh and they can also figure out how likely a customer is to leave or if they're ready to shop again!

**KEYWORDS:** Shopping Mall, Revenue Real-Time, Customization, Digital Coupons, Customer Engagement, Personalized Marketing.

## I. INTRODUCTION

With big data & deep learning technology growing, new opportunities in marketing have emerged This shift is part of management, and it's super exciting. Also, as more people use the internet, digital coupons have become a popular to promote products [1]. Issuing customized digital coupons is key for online businesses. Why? Because keeping current customers is more crucial than bringing in new ones [2]. It's also cheaper to keep existing customers [3]. In, it costs anywhere from five to six times more to get new customers than to maintain ones you already have [4]. Companies that manage to reduce customer churn by improving retention not only see better profits but also boost their brand image by keeping customers happy [5].

Research into customized coupon issuance has been particularly active in competitive fields like telecommunications, finance, distribution, & gaming industries. It mainly focuses on creating predictive models with machine learning & AI technology [6]. Recently, there's been a rise in AI- based marketing that uses big data analysis and deep learning. This AI-driven approach can significantly lower marketing expenses & increase online sales if it accurately estimates how customers respond [7].

For online shopping malls, the average conversion rate for purchases hovers around 2%. It's easy for shoppers to browse quickly on their PCs or mobiles—sometimes too easy! Customers can easily come & go in just a moment. So even a tiny decrease in customer churn can boost conversions and bring in big profits. Unlike offline stores, online shops collect data effortlessly. They capture every single behavior of their online customers right away. This means they end up with tons of history about their customers that helps them understand preferences.

If businesses use this rich historical data wisely—inferring behaviors and tastes—they can ramp up conversion rates without needing extra promotions. One very straightforward way is by issuing personalized coupons instantly to shoppers. By targeting customers at risk of leaving and giving them special discount codes on the spot, sales can jump without additional promotional costs like events might incur.

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For this strategy to work effectively, an AI-powered approach is essential. Once AI learns from customer data automatically, it can decide when and how to issue coupons based on individual preferences. Deep learning strategies are particularly well-suited here because they dig deep into the data pile and find patterns—more data usually leads to better outcomes! Daily updates keep refining these models too.

When we talk about AI-based coupon methods, there are mainly three categories: customer segmentation, churn prediction, & personalized recommendations. Customer segmentation sorts individuals based on shared traits—the starting point for tailored marketing strategies for different groups [8]. Machine learning tools used for this often include supervised methods like decision trees or unsupervised methods such as K-means models or self-organizing maps (SOMs) [9]. Recent work highlights that customer segmentation often ties into other marketing research areas too, like predicting who might churn [10], [11].

Customer churn prediction itself is a hot topic in marketing studies using machine learning. Good churn predictions are vital—not just for sales but for broader company strategies too [4]. With more customers leaving due to fierce competition today, many researchers are busy developing new models that predict churn effectively.

In earlier studies, researchers often relied on single algorithms like decision trees or logistic regression to look for shifts in customer behavior. Slowly but surely, there's now a trend toward ensemble models that connect different algorithms together [12]. On another note, systems for personalized recommendations are also booming alongside churn prediction studies [13]. There's more focus on improving recommendations on sites like Amazon and Netflix nowadays.

Customized coupon issuance has much potential for online shops! Because user traffic in these malls can change so fast compared to physical stores, old school discount tactics don't quite cut it anymore online. Collecting more log data online opens up unique marketing opportunities via AI—helping create instant checkout strategies!

Typically, studies look at all customers as one big group & make predictions across the board at once. But in reality? Everyone behaves differently based on various transaction habits – no two shoppers are alike! Thus it makes sense that using distinct AI models for smaller groups of similar- minded shoppers could be much more powerful.

In this study specifically using deep learning with real-time clickstream data to identify at-risk customers—we aim to issue custom coupons matching their preferences. Here are the highlights: Firstly, we've segmented customers properly & built tailored models for predicting churn based on each group's features. Secondly, we created a real-time model predicting customer churn risks from clickstream data using deep learning technologies.

Thirdly—most importantly—we've successfully raised actual conversion rates by issuing personalized coupons directly through our shopping site. Unlike previous research efforts—our project stands out by assessing transactions as they happen with gathered live data while navigating these three crucial steps against runaway customer loss.

Lastly? We tested our model across various scenarios showcasing its economic advantages across actual mall environments! This paper is neatly organized into sections: Section II covers various existing research efforts; Section III lays out our methodology; Section IV explains how we applied this method within real shopping platforms; Section V shares experimental results backing this research's validity; and finally Section VI wraps things up with conclusions drawn from all our findings!

So there you go! Exciting advances in the world of marketing done right with friendly AI help!

## II. LITERATURE REVIEW

RELATED WORK The modern retail landscape has evolved significantly with the advent of digital technologies, prompting shopping malls to adopt innovative strategies to enhance customer engagement and revenue. Among these strategies, the issuance of personalized digital coupons in real-time stands out as a powerful tool for driving consumer spending and improving mall income. This literature survey explores various dimensions of this approach, examining the underlying technologies, consumer behavior, and the overall impact on mall revenues. Personalized marketing has become a cornerstone of contemporary retail strategies, driven by the understanding that tailored interactions significantly influence consumer behavior. Several studies have highlighted the effectiveness of personalization in fostering customer loyalty and enhancing shopping experiences. For instance, Ranjan and Read (2016) demonstrated that personalized offers are more likely to lead to purchase decisions compared to generic promotions. In the context of

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shopping malls, real-time customization of digital coupons allows retailers to deliver highly relevant discounts and promotions, thereby increasing the likelihood of immediate purchases. Real-Time Technologies and Data Analytics The deployment of real-time personalized digital coupons relies heavily on advanced technologies such as big data analytics, machine learning, and mobile communication. According to Chen et al. (2018), the integration of these technologies enables malls to analyze vast amounts of consumer data in real-time, including purchase history, browsing behavior, and location data. This capability allows for the dynamic generation of personalized offers that are tailored to individual preferences and current shopping contexts. Moreover, mobile technologies play a crucial role in delivering these coupons instantly to customers, enhancing the immediacy and relevance of the promotions. Consumer Behavior and Coupon Redemption Understanding consumer behavior is crucial for the successful implementation of personalized digital coupons. Studies by Li and Kannan (2014) have shown that consumers are more responsive to promotions that are relevant to their immediate needs and preferences. Real-time digital coupons cater to this by providing offers that are not only personalized but also timely, matching the consumer's shopping journey. Furthermore, the instant delivery of these coupons via mobile devices ensures that the offers are readily accessible, increasing the likelihood of redemption. The convenience and relevance of these digital coupons can significantly influence purchasing decisions, thereby boosting mall revenue. Impact on Mall Revenue and Customer Retention The impact of personalized digital coupons on mall revenue is multifaceted. According to Zhang et al. (2019), malls that implement real-time personalized coupon strategies often experience a notable increase in foot traffic and sales. The personalization of offers enhances customer satisfaction and loyalty, encouraging repeat visits and sustained spending. Additionally, the immediate nature of real-time coupons can prompt spontaneous purchases, further driving revenue growth. The overall improvement in customer retention and engagement also contributes to a steady increase in long-term income for malls. While the benefits of personalized digital coupons are clear, there are challenges that malls must address to optimize their implementation. Privacy concerns and data security are significant issues, as consumers may be wary of sharing personal information necessary for coupon personalization (Acquisto et al., 2015). Malls need to ensure robust data protection measures and transparent privacy policies to build consumer trust. Moreover, the effectiveness of digital coupons depends on the accuracy and timeliness of the underlying data analytics, necessitating continuous investment in advanced technology and skilled personnel.In conclusion, the issuance of personalized digital coupons in real-time represents a compelling strategy for enhancing mall revenue by fostering consumer engagement and promoting increased spending. The integration of advanced technologies such as big data analytics and mobile communication plays a critical role in the successful deployment of these personalized offers. While challenges such as privacy concerns and the need for accurate data analytics remain, the potential benefits in terms of increased foot traffic, sales, and customer loyalty underscore the importance of adopting this innovative approach. As shopping malls continue to navigate the evolving retail landscape, personalized digital coupons will likely remain a key component of their revenue enhancement strategies.

## III. 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 autoencoder. A typical example is the sequential method of applying cluster analysis after dimensionality reduction using an autoencoder [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

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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 content-based 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.

## IV. PROPOSED SYSTEM

In this study, applying deep learning techniques to real-time click stream data, we find customers with high chance of churning rates and issue a coupon that suits customers' preferences. This study has the following significance: First, we segmented the customer and develop a suitable model for customer churn pre- diction for each segmentation. Second, we made a clickstream-based real- time customer churn risk pre- diction model using deep learning models. Third, we improved the actual conversion rate by issuing customized coupons in real shopping mall website.

Unlike other studies, the scientific contribution of this study was to analyze customers in real time using data collected in real time as well as going through three steps to prevent customer churn. Also, we applied our model to the actual shopping mall, demonstrating the economic effectiveness and efficiency of the three steps of our model.

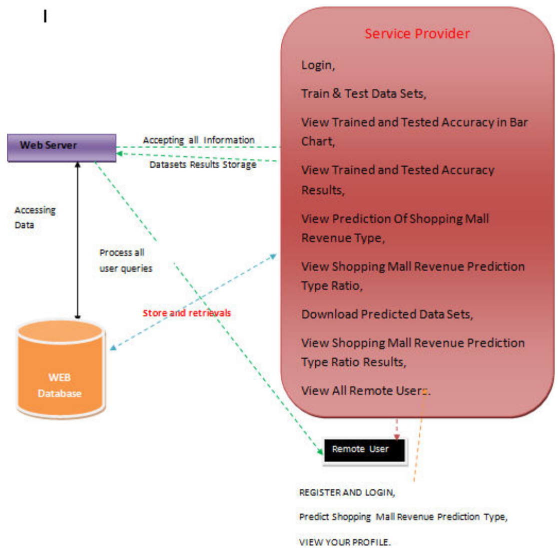


Fig :1 Proposed Architecture

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## V. MODULE DESCRIPTION

IMPLEMENTATION
Multi-Layer Perceptron (MLP) 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 asTrain & 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.

Decision tree classifiers
Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision-making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:
Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class
Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

Gradient boosting
Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient- boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

K-Nearest Neighbors (KNN)
Simple, but a very powerful classification algorithm Classifies based on a similarity measure
Non-parametric Lazy learning
Does not "learn" until the test example is given
Whenever we have a new data to classify, we find its K-nearest neighbors from the training data Example
Training dataset consists of k-closest examples in feature space
Feature space means, space with categorization variables (non-metric variables)
Learning based on instances, and thus also works lazily because instance close to the input vector for test or prediction may take time to occur in the training dataset

Logistic regression Classifiers
Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name logistic regression is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name multinomial logistic regression is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.Logistic regression competes with discriminant analysis as a method for analyzing categorical-response

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variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

Naïve Bayes

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature .Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique.Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b and RapidMiner 4.6.0). We try above all to understand the obtained results.

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg. An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance.

Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an independent and identically distributed (iid) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point x and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.SVM is a discriminant technique, and, because it solves the convex optimization

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problem analytically, it always returns the same optimal hyperplane parameter—in contrast to genetic algorithms (GAs) or perceptrons, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

## VI. RESULTS

Enhancing real-time income at malls through the issuance of personalized digital coupons represents a promising strategy that marries technology with consumer psychology to boost revenue and improve customer loyalty. As shopping malls face increasing competition from e- commerce and changing consumer preferences, innovative approaches such as real-time digital couponing can play a pivotal role in attracting and retaining customers, driving sales, and ultimately enhancing the mall's profitability.Real-Time Personalization and Consumer EngagementOne of the key advantages of personalized digital coupons is their ability to engage customers in a highly targeted manner. By leveraging data analytics and customer behavior insights, malls can deliver tailored offers that resonate with individual shoppers. This level of personalization can range from basic demographic targeting to more sophisticated techniques that consider purchasing history, browsing behavior, and even real-time location within the mall. For example, a customer who frequently shops for electronics may receive a digital coupon for a discount at an electronics store just as they approach it. This real-time, context-aware approach not only increases the likelihood of immediate redemption but also enhances the overall shopping experience by making it more relevant and engaging.Boosting Sales Through Dynamic Discounts Personalized digital coupons can significantly boost sales by offering dynamic discounts that respond to real-time factors such as inventory levels, time of day, or seasonal demand. For instance, if a particular store is experiencing low foot traffic or has excess inventory of a certain product, the mall's digital coupon system can automatically generate and distribute targeted discounts to attract customers to that store. This not only helps in clearing stock but also creates a sense of urgency among shoppers, encouraging them to make spontaneous purchases that they might have otherwise postponed or foregone.Enhancing Customer Loyalty and Repeat Visits By consistently offering valuable and personalized incentives, malls can foster greater customer loyalty and encourage repeat visits. Digital coupons can be integrated into a broader loyalty program, where customers earn rewards or receive special offers based on their shopping behavior and frequency of visits. This not only incentivizes customers to return but also helps malls gather valuable data on shopping patterns, preferences, and trends. Over time, this data can be used to refine marketing strategies, enhance the effectiveness of promotions, and ultimately drive sustained revenue growth.Leveraging Mobile Technology for Immediate ImpactThe ubiquity of smartphones provides a powerful platform for delivering personalized digital coupons directly to consumers. Malls can leverage mobile apps, SMS, and email notifications to ensure that shoppers receive timely and relevant offers. Geo-fencing technology can further enhance this by triggering coupon notifications when a customer enters a specific area of the mall. This immediate, location- based approach increases the likelihood of coupon redemption and drives foot traffic to specific stores or areas within the mall, contributing to a more dynamic and profitable shopping environment.Data-Driven Decision Making and Continuous Improvement The implementation of personalized digital coupons offers malls a wealth of data that can be analyzed to inform decision- making and optimize marketing efforts. By tracking coupon redemptions, purchase patterns, and customer feedback, malls can gain deep insights into what drives customer engagement and sales. This data-driven approach allows for continuous improvement, as marketing campaigns can be adjusted in real-time based on their performance. For example, if a particular type of coupon is not performing well, the mall can quickly pivot to a different offer or adjust the targeting criteria to improve results.Overcoming Challenges and Ensuring Success While the benefits of personalized digital coupons are clear, there are also challenges to consider. Ensuring data privacy and security is paramount, as customers need to trust that their personal information is being handled responsibly. Malls must also invest in the necessary technology infrastructure and develop partnerships with retailers to ensure seamless integration and effective execution of coupon campaigns. Additionally, ongoing staff training and customer education are essential to maximize the effectiveness of the digital coupon system and to ensure that both employees and shoppers understand how to take full advantage of the available offers.

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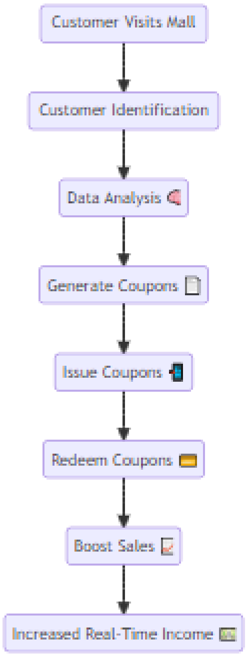


Fig : 2 Results

## VII. CONCLUSION

We identified previous e-commerce marketing approaches to derive user behavior prediction. A deep learning method for real time customer churn prediction showed an appropriate result. We applied our research to online shopping mall to raise conversion rate and sales. To check whether our experiment carry out monetary value, we developed a framework to measure the sales amount when used with segment model and personalized recommended digital coupon. We found that our model (scenario1) shows the best results. We found it is suitable for e-commerce online shopping mall to raise conversion rate and sales. Our study empirically showed that marketing, which was a field of management, could be solved more efficiently and quickly by applying big data and deep learning technology.

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