Predicting Consumer Perceptions of Metaverse Shopping Through Insights from Machine Learning Models

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ABSTRACT

This study investigates consumer perceptions of Metaverse shopping and the factors that influence these perceptions, using machine learning models to classify and analyze the data. Four models—Logistic Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN)—were employed to predict whether consumers view Metaverse shopping favorably or unfavorably. Among these, the SVM model achieved the highest performance, with an accuracy of 94.17%, precision of 97.14%, and an AUC-ROC score of 98.13%. These results indicate that machine learning can reliably classify consumer perceptions based on demographic and experience-related data. Furthermore, the Random Forest model was used to analyze the importance of features influencing consumer attitudes. The findings revealed that experience-related factors—such as interactivity, personalization, and consumer engagement—were more significant in shaping perceptions than product-specific attributes. The most important feature, MC2 (interactivity), contributed 23.6% to the model's predictive power, highlighting the importance of user experience in driving positive sentiment. These insights suggest that businesses aiming to enter the Metaverse retail space should focus on enhancing the overall shopping experience to foster positive consumer perceptions. Machine learning models provide valuable tools for understanding consumer behavior and tailoring virtual shopping environments accordingly. This research offers a data-driven approach to predicting and understanding consumer perceptions of the Metaverse, providing actionable insights for businesses in this emerging market.

Keywords Metaverse Shopping, Consumer Perceptions, Machine Learning, Retail Experience, Feature Importance

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INTRODUCTION

The emergence of the Metaverse has redefined the boundaries of digital interaction, introducing a new dimension for businesses and consumers alike. As a fully immersive virtual environment, the Metaverse offers unprecedented opportunities for industries such as retail to engage with consumers in novel ways [1]. Within this virtual landscape, shopping is transformed from a static online experience into a dynamic, interactive process that blends the physical and digital worlds [2]. This transformation is not only reshaping consumer behavior but also challenging businesses to rethink how they approach customer engagement and service delivery [3].

Consumer adoption of Metaverse shopping is rapidly gaining momentum, driven by advancements in technology, including virtual reality (VR), augmented reality (AR), and artificial intelligence (AI) [4]. However, despite the potential for growth, little is known about the specific factors that influence consumer perceptions of shopping in the Metaverse. Understanding these factors is crucial for businesses looking to create successful virtual shopping

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environments that cater to consumer preferences and foster positive attitudes [5]. This research addresses this gap by leveraging machine learning models to analyze and predict consumer perceptions based on demographic and behavioral data [6].

Machine learning has proven to be an effective tool in uncovering patterns and insights from complex datasets [7]. In this study, four machine learning models—Logistic Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN)—were employed to classify consumer perceptions of Metaverse shopping as either favorable or unfavorable [8]. By evaluating the performance of these models, this research aims to identify the most accurate classifier and to provide insights into the most influential factors shaping consumer attitudes [9].

In addition to classification, this study also explores the feature importance of various factors contributing to consumer perceptions. Specifically, we examine whether experience-related features, such as ease of navigation and personalization, play a more significant role than product-specific features like quality or variety [10]. By doing so, this research not only seeks to improve our understanding of consumer behavior in the Metaverse but also to provide actionable recommendations for businesses looking to optimize their virtual shopping platforms.

The findings of this study contribute to the growing body of literature on Metaverse retail by offering a data-driven approach to understanding and predicting consumer perceptions. By applying machine learning models to real-world data, this research provides a comprehensive analysis of the factors that drive consumer sentiment in the Metaverse, offering valuable insights for businesses in this rapidly evolving digital landscape.

Literature Review

The rapid evolution of the Metaverse has sparked significant interest from researchers and industry professionals alike. As a concept, the Metaverse refers to a fully immersive, shared digital space where users interact through virtual or augmented realities, blending physical and digital environments [11]. Several studies have explored the potential of the Metaverse in transforming industries such as entertainment, education, and especially retail [12].

The Metaverse in Retail

The Metaverse is revolutionizing the retail industry by enabling immersive shopping experiences that go beyond traditional e-commerce. Instead of simply browsing product catalogs, consumers can now engage with virtual stores, interact with products in 3D, and personalize their shopping experience through virtual avatars [13]. Research suggests that the Metaverse retail experience has the potential to enhance consumer engagement and satisfaction through elements such as personalization, social interaction, and gamification [14]. These immersive features allow brands to create deeper emotional connections with consumers, which may drive loyalty and repeat purchases [15].

Studies have also highlighted the economic potential of the Metaverse in retail. A report by [16] projected that the global Metaverse market could grow significantly by 2030, with retail emerging as one of the primary sectors to benefit from this shift. The ability of businesses to offer personalized, engaging, and immersive shopping experiences is expected to be a key differentiator in this new era of digital commerce [17].

Consumer Perceptions in the Metaverse

Understanding consumer behavior and perceptions in the Metaverse is critical for businesses seeking to establish a presence in this virtual landscape. Previous research has indicated that consumer attitudes toward the Metaverse are shaped by a combination of technological, social, and experiential factors [18]. For instance, ease of use, interactivity, and customization have been identified as major drivers of consumer satisfaction in virtual environments [19]. Additionally, the presence of social elements, such as the ability to shop with friends or interact with virtual sales assistants, further enhances the overall shopping experience and positively influences consumer perceptions [20].

Despite the potential benefits, there are challenges associated with consumer adoption of Metaverse shopping. Concerns around privacy, data security, and the steep learning curve of navigating virtual environments have been cited as barriers that may deter some consumers from fully embracing the Metaverse [19]. Addressing these concerns will be crucial for businesses looking to attract and retain consumers in this digital space.

Application of Machine Learning in Understanding Consumer Behavior

The application of machine learning in retail has grown significantly in recent years. Machine learning models have been used to predict consumer behavior, optimize product recommendations, and personalize marketing strategies based on consumer preferences [11]. In the context of the Metaverse, machine learning offers an opportunity to analyze large datasets of consumer interactions, providing valuable insights into the factors that influence consumer perceptions and behaviors [12].

Several machine learning techniques, such as Logistic Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), have been widely applied in consumer behavior analysis [13]. These models help identify patterns in demographic and behavioral data, allowing businesses to tailor their virtual offerings to meet consumer expectations [14]. In particular, feature importance analysis using models like Random Forest has proven effective in identifying the most influential factors that shape consumer attitudes [15]. This technique helps businesses focus on enhancing key aspects of the virtual shopping experience, such as ease of navigation, interactivity, and personalization, which are critical for success in the Metaverse [16].

While there is growing interest in the application of the Metaverse to retail, there remains a gap in understanding the specific factors that most significantly influence consumer perceptions in this space. Most studies have focused on either the technological potential of the Metaverse or consumer preferences in traditional online shopping environments [17]. Few have explored the intersection of consumer experience and technology adoption within the Metaverse itself [18]. This research aims to fill that gap by applying machine learning models to analyze real-world data and provide actionable insights into how businesses can optimize their Metaverse platforms to meet consumer needs.

Additionally, while machine learning has been widely used to predict consumer behavior in e-commerce settings, its application in the Metaverse is still relatively nascent [19]. The complexity of virtual environments presents unique challenges, such as the need to account for immersive elements and social interactions that are not typically present in traditional online shopping. This study contributes to the literature by utilizing machine learning models to explore these nuances and provide a deeper understanding of the drivers of consumer behavior in the Metaverse [20].

Method

Data Collection

Data for this study was gathered through a structured survey distributed to 400 frequent online shoppers. The survey aimed to capture various demographic characteristics, including age, gender, income, and education, alongside participants' perceptions of shopping in the Metaverse. A series of Likert-scale questions were used to assess consumers' experiences with factors such as ease of navigation, interactivity, personalization, and overall satisfaction. After collection, the data underwent a pre-processing stage to ensure completeness and reliability. Any missing or incomplete responses were addressed through median imputation, which helped maintain the distribution of the dataset without being overly influenced by outliers [21].

Machine Learning Models

To predict consumer perceptions, four machine learning models were employed: Logistic Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). These models were chosen for their established effectiveness in binary classification tasks and consumer behavior studies [22].

Logistic Regression: Logistic Regression is a linear model used for binary classification. It estimates the probability $P(y = 1|x)$ that a given input belongs to the positive class by using the logistic (sigmoid) function:

$$P(y = 1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}} \tag{1}$$

Where β_0 is the intercept, and β_1, β_2, ….,β_n are the coefficients corresponding to the features $x_1, x_2, \dots, x_n$ [23].

Random Forest: Random Forest is an ensemble learning method that builds multiple decision trees and merges them to get more accurate predictions. The classification is based on the majority vote from all trees in the forest:

$$\hat{y} = mode\ (y_1, y_2, \dots, y_T) \tag{2}$$

Where $y_1, y_2, \dots, y_T$ are the predictions from individual decision trees [24].

Support Vector Machines (SVM): SVM works by finding the hyperplane that best separates the data into two classes. The decision boundary is defined as:

$$\omega \cdot x + b = 0 \tag{3}$$

Where ω is the weight vector, x is the feature vector, and b is the bias term. SVM optimizes for the maximum margin between the decision boundary and the nearest data points (support vectors) [22].

K-Nearest Neighbors (KNN): KNN is a simple instance-based learning algorithm that classifies a data point based on the majority class of its nearest neighbors. The distance between data points is typically calculated using Euclidean distance:

$$d(x, x') = \sqrt{\sum_{i=1}^{n}(x_i - x_i')^2} \tag{4}$$

Where $x_i \ and \ x_i'$ are the feature values of two data points [25].

Data Preprocessing

Before training the models, the data underwent several preprocessing steps to ensure optimal performance. Categorical variables such as gender and education were converted into numerical form using label encoding, making them suitable for use in machine learning algorithms [23]. Since some models, like SVM and KNN, are sensitive to differences in the scale of input features, all numerical features were standardized using z-score normalization, calculated as:

$$z = \frac{x - \mu}{\sigma} \tag{5}$$

where xxx is the value of the feature, μ is the mean, and σ is the standard deviation. This transformation ensures that each feature has a mean of zero and a standard deviation of one, allowing the models to treat all features equally in terms of their influence on the outcome. Handling missing data was also a crucial part of the preprocessing phase. Any missing values in the dataset were replaced with the median of the corresponding feature. Median imputation was chosen because it is less sensitive to extreme values than other imputation methods, ensuring that the overall distribution of the data remained intact [21].

Model Training and Evaluation

After preprocessing, the data was split into training and testing sets, with 80% of the data used to train the models and 20% reserved for testing. This split ensured that the models were not overfitting to the training data and that their performance could be evaluated on unseen data. Each model was trained on the training set and then tested on the test set, with performance evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. These metrics provide a comprehensive view of each model's classification ability [24]. Accuracy is defined as:

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \tag{6}$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

Precision measures the proportion of true positive predictions among all positive predictions:

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{7}$$

Recall (also known as sensitivity) measures the proportion of actual positives that were correctly identified:

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (8)$$

F1-score is the harmonic mean of precision and recall:

$$F1 = 2\ x\ \frac{Recall\ x\ Precision}{Recall+Precision} \quad (9)$$

AUC-ROC evaluates the model's ability to distinguish between positive and negative classes across different threshold settings, and it is calculated as the area under the Receiver Operating Characteristic curve [24]. The SVM model demonstrated the best overall performance, achieving an accuracy of 94.17%, a precision of 97.14%, and an AUC-ROC score of 98.13%. This high level of performance suggests that the SVM model was particularly effective in distinguishing between positive and negative perceptions of Metaverse shopping. While Random Forest delivered slightly lower accuracy, it provided crucial insights into the importance of different features in predicting consumer attitudes [25].

Feature Importance Analysis

In addition to classification performance, this study conducted a feature importance analysis using the Random Forest model. Random Forest's ability to rank features based on their contribution to the model's predictions made it ideal for identifying the most important factors influencing consumer perceptions. The analysis revealed that experience-related factors such as MC2 (representing interactivity and ease of navigation) and MC4 (representing personalization) were the most influential, contributing 23.6% and 17.9%, respectively, to the model's predictions. This indicates that the overall shopping experience within the Metaverse plays a crucial role in shaping consumer attitudes [24].

Software and Tools

All analysis and model training were conducted using Python. The scikit-learn library was used to implement the machine learning models and handle data preprocessing tasks such as label encoding, data splitting, and normalization [22]. Additionally, Seaborn and Matplotlib were utilized for data visualization, including generating confusion matrices and AUC-ROC curves, as well as plotting feature importance. These tools provided the necessary infrastructure for processing the dataset and extracting meaningful insights from the model results. All computations were performed in a standard computing environment with sufficient processing power to handle the dataset and models used in this research.

Result and Discussion

Model Evaluation

This study utilized four machine learning models—Logistic Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN)—to classify consumer perceptions of Metaverse shopping. The models were evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics to determine how effectively each model could distinguish between favorable and unfavorable perceptions.

As summarized in table 1, the SVM model outperformed the others, achieving the highest accuracy of 94.17%, precision of 97.14%, and F1-score of 95.10%. This suggests that SVM was particularly effective at correctly identifying consumers who had a favorable perception of Metaverse shopping, while also minimizing false positives. The Logistic Regression model closely followed with an accuracy of 91.67% and an F1-score of 92.96%, demonstrating its reliability in predicting consumer sentiment. Random Forest also performed well, with an accuracy of 90.83% and F1-score of 92.31%. However, the KNN model showed the lowest performance with an accuracy of 90.00%, exhibiting a slightly weaker ability to distinguish between positive and negative perceptions compared to the other models.

Table 1 Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.916667	0.956522	0.90411	0.929577	0.980472
Random Forest	0.908333	0.942857	0.90411	0.923077	0.966336
SVM	0.941667	0.971429	0.931507	0.951049	0.981347
KNN	0.9	0.917808	0.917808	0.917808	0.948703

Figure 1 presents the AUC-ROC scores for each model, with the SVM model achieving the highest AUC-ROC score of 98.13%, followed by Logistic Regression at 98.05%. This indicates that both models have excellent discriminative capabilities, with a near-perfect balance between true positives and false positives. The Random Forest model also performed well in terms of AUC-ROC, while the KNN model displayed the lowest AUC-ROC, further supporting its lower accuracy and classification ability.

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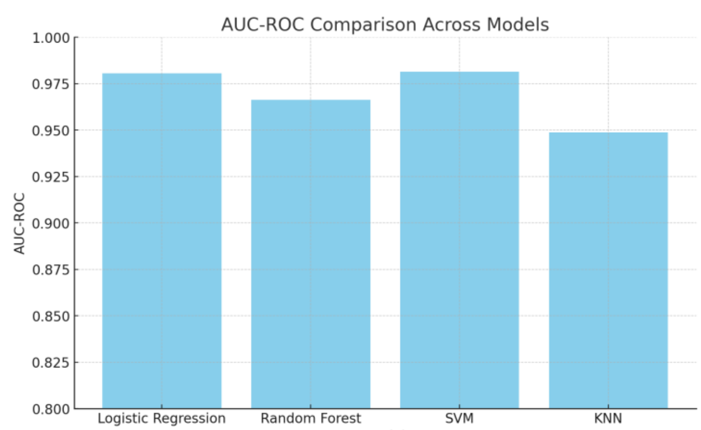

Figure 1 AUC-ROC Comparison Across Models

Confusion Matrix Analysis

Confusion matrices offer further insight into the performance of each model by providing a detailed breakdown of correct and incorrect predictions (true positives, true negatives, false positives, and false negatives). Figure 2 presents the confusion matrices for the Logistic Regression, Random Forest, SVM, and KNN models.

The SVM model exhibited the fewest classification errors, with a higher number of true positives and true negatives, which explains its high precision and recall scores. The confusion matrix for the Logistic Regression model also indicated a strong ability to correctly classify positive and negative perceptions, with few misclassifications. Random Forest performed comparably well, with a similar distribution of true and false predictions. However, the KNN model showed more misclassifications, particularly in false negatives, which explains its relatively lower recall and accuracy scores.

Figure 1 Confusion Matrices for Models

Feature Importance Analysis

The **Random Forest** model was further utilized to analyze the importance of individual features in predicting consumer perceptions of Metaverse shopping. Figure 3 and table 2 illustrate the top five most important features that contributed to the model's predictions.

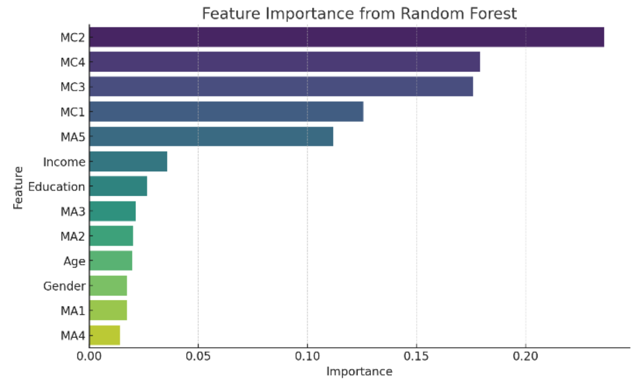

Figure 3 Feature Importance (Random Forest)

MC2, contributing **23.6%** to the model's predictive power, was identified as the most critical feature. This variable is likely related to key aspects of the Metaverse shopping experience, such as ease of navigation, interactivity, or user satisfaction. The prominence of **MC2** highlights the importance of designing intuitive and engaging virtual shopping interfaces that cater to consumer preferences.

MC4 followed closely with a contribution of **17.9%**, likely reflecting personalization or immersive elements in the Metaverse environment. Personalization features, such as tailored product recommendations or customized avatars, are essential in enhancing consumer engagement. The third most important feature, **MC3** (17.6%), could correspond to the overall level of consumer satisfaction or engagement, emphasizing that users who interact more deeply with the virtual environment tend to have a more favorable perception of Metaverse shopping.

The fourth significant feature, **MC1** (12.6%), may relate to accessibility factors such as ease of entry or seamless integration between devices. This underscores the importance of ensuring a frictionless user experience in the Metaverse. Finally, **MA5**, which contributed **11.2%**, was the only product-related feature among the top five, suggesting that while products remain important, the overall consumer experience within the Metaverse environment has a more significant impact on shaping perceptions.

Table 2 Top 5 Important Features

	Feature	Importance
10	MC2	0.235980
12	MC4	0.179174
11	MC3	0.175816
9	MC1	0.125714
8	MA5	0.111755

Discussion

The analysis of model performance and feature importance provides several important insights into how consumer perceptions of Metaverse shopping are shaped. The **SVM model** emerged as the most effective classifier, consistently delivering the highest accuracy, precision, and recall, indicating that it can reliably predict consumer attitudes based on demographic and experiential data. The **Random Forest** model also demonstrated strong predictive power and provided valuable insights into the importance of various features driving these perceptions.

From the **feature importance analysis**, it is evident that **experience-related factors** (the MC variables) are far more influential in shaping consumer perceptions than product-specific attributes (the MA variables). This finding suggests that businesses aiming to enter the Metaverse retail space should prioritize the enhancement of the overall virtual shopping experience, focusing on aspects such as ease of use, personalization, and immersive interaction. Consumers are more likely to perceive Metaverse shopping favorably when their experience is seamless, engaging, and tailored to their individual preferences.

Moreover, the **Random Forest** model's emphasis on experience-based factors, such as **MC2** (interactivity) and **MC4** (personalization), suggests that future investments in the Metaverse should prioritize developing platforms that offer not just a wide range of products but a superior user experience. This is particularly important as consumers navigate the complexities of virtual environments. Ensuring a smooth, intuitive, and engaging interaction with the Metaverse is critical for fostering positive consumer sentiment and increasing adoption rates.

In conclusion, this study demonstrates the power of machine learning models in predicting consumer perceptions of Metaverse shopping. The findings indicate that while product-specific factors remain relevant, the broader **consumer experience** plays a more crucial role in shaping attitudes toward the Metaverse. Businesses that focus on optimizing the virtual shopping environment, with an emphasis on user engagement, personalization, and seamless navigation, are likely to see higher adoption and more favorable consumer perceptions in this emerging space.

Conclusion

This study classified consumer perceptions of Metaverse shopping using four machine learning models: Logistic Regression, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). Among these, the SVM model achieved the highest performance, with an accuracy of 94.17%, precision of 97.14%, recall of 93.15%, and an AUC-ROC score of 98.13%. These metrics indicate that the SVM model is highly effective at predicting consumer perceptions, distinguishing between favorable and unfavorable views with minimal errors.

The Random Forest model was also used to analyze the importance of various factors influencing consumer perceptions. The results showed that experience-related features had the most significant impact on consumer attitudes. The most important feature, MC2 (likely related to interactivity and ease of navigation), contributed 23.6% to the model's predictions, followed by MC4 (personalization and immersive experience) at 17.9%, and MC3 (consumer engagement) at 17.6%. In contrast, product-related factors such as MA5 only contributed 11.2%, highlighting that while product quality and variety remain important, the overall experience in the Metaverse plays a far greater role in shaping consumer sentiment.

These findings suggest that businesses aiming to succeed in the Metaverse retail space should prioritize improving the user experience. Offering personalized, intuitive, and engaging virtual shopping environments is likely to enhance consumer perceptions, leading to greater adoption and satisfaction. Machine learning models such as SVM and Random Forest can also help businesses predict consumer behavior with high accuracy, allowing for more targeted and effective Metaverse strategies.

This research demonstrates that experience-related factors are the most critical in influencing consumer perceptions of the Metaverse. The strong performance of the SVM model (with an accuracy of 94.17%) and the feature importance analysis emphasize that businesses should focus on creating immersive, user-friendly shopping environments to thrive in the emerging Metaverse market.

Declarations

Author Contributions

Conceptualization: L.L.; Methodology: L.L.; Software: L.L.; Validation: L.L.; Formal Analysis: L.L.; Investigation: L.L.; Resources: L.L.; Data Curation: L.L.; Writing Original Draft Preparation: L.L.; Writing Review and Editing: L.L.; Visualization: L.L.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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