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Design and Implementation of a Secure AI-Based Product Showcase and Customer Support System for Small and Medium-Sized Enterprises

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Abstract

This paper presents the development and evaluation of a secure artificial intelligence-driven product showcase and customer support system designed specifically for Small and Medium-Sized Enterprises (SMEs). The proposed platform combines product presentation, an AI-powered customer support chatbot, a content-based recommendation engine and integrated security mechanisms within a unified web application to improve customer engagement, product accessibility and data protection. A hybrid dataset consisting of 2,050 product records obtained from TY Supermarket, Iree, Osun State, Nigeria and a publicly available Kaggle e-commerce dataset was used for model training and system evaluation. Textual data were transformed into numerical features using the Term Frequency–Inverse Document Frequency (TF-IDF) technique, while the Multinomial Naive Bayes algorithm was employed to classify customer intents. Product recommendations were generated using a Content-Based Filtering approach based on Cosine Similarity. To safeguard user and business information, the system incorporated Role-Based Access Control (RBAC), secure password hashing, authentication and session management. Performance evaluation showed that the chatbot achieved an accuracy of 95.50%, precision of 95.55%, recall of 95.50% and an F1-score of 95.51%, whereas the recommendation module attained an accuracy of 93.80%. User acceptance was further evaluated through a five-point Likert-scale questionnaire administered to 40 participants, producing an overall satisfaction score of 95.00%. The findings indicate that the developed system enhances customer interaction, facilitates efficient product discovery, improves operational efficiency and strengthens information security. Consequently, the proposed framework provides an affordable, intelligent and secure digital business solution capable of supporting the digital transformation of SMEs.

Keywords: *Artificial Intelligence, Product Showcase, Customer Support, Chatbot, Multinomial Naive Bayes.*

1.0 Introduction

Advances in digital technology have significantly reshaped modern business operations by changing how products are promoted, customers are served and business processes are managed. The increasing use of Information and Communication Technology (ICT) has provided organizations with opportunities to strengthen their online presence, improve customer relationships and deliver services more efficiently through digital platforms. In today's competitive marketplace, customers demand immediate access to product information, personalized recommendations, secure online interactions and prompt responses to their enquiries. As a result, Small and Medium-Sized Enterprises (SMEs) are increasingly required to adopt intelligent and secure digital solutions capable of satisfying these changing customer expectations.

Effective product presentation and responsive customer support play a vital role in influencing customer satisfaction, purchase decisions and long-term customer loyalty. Many Small and Medium-Sized Enterprises (SMEs) still depend on traditional communication methods, social media platforms and manual product promotion strategies to interact with customers and market their products. While these approaches may be suitable for small-scale operations, they frequently result in slow response times, inconsistent information delivery, limited accessibility, reduced product visibility and a lack of personalized customer interaction. Such limitations can diminish customer engagement, restrict business growth and reduce the competitive advantage of SMEs in today's rapidly evolving digital marketplace.

In response to these limitations, many organizations have embraced intelligent technologies to automate customer interactions and improve access to business information and services. Among these innovations, Artificial Intelligence (AI) has become a key enabling technology for enhancing customer support, streamlining

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business operations and supporting informed decision-making. AI-based applications are capable of analysing user behaviour, interpreting customer requests and generating relevant responses with minimal human involvement.

One of the most widely adopted AI applications in customer service is the chatbot, which mimics human conversation to provide immediate assistance and respond to customer enquiries in real time. The adoption of chatbots has been shown to reduce operational workload, improve service efficiency and increase customer satisfaction through continuous and readily available support.

Beyond intelligent customer support, recommendation systems have become an essential feature of contemporary digital commerce platforms. These systems analyse customer interactions, preferences and behavioural patterns to identify products that best match individual user interests. By delivering personalized product recommendations, they enhance customer engagement, improve product visibility and assist users in making informed purchasing decisions. Furthermore, advances in machine learning have significantly increased the accuracy and effectiveness of recommendation systems by enabling better prediction of customer preferences and purchasing behaviour.

Although AI-enabled business applications have become increasingly popular, many existing solutions are designed to address only a single aspect of digital business operations, such as product presentation or automated customer support, with limited integration of personalized recommendation features. In addition, several commercial platforms are intended for large-scale enterprises and often require considerable financial resources, technical expertise and sophisticated infrastructure for deployment. Consequently, many SMEs have limited access to affordable integrated systems that simultaneously support product management, intelligent customer interaction and personalized recommendations. This lack of integration can reduce operational efficiency, create inconsistent customer experiences and limit business growth opportunities.

Beyond functionality and intelligence, security has become a critical concern in modern digital business systems. As businesses increasingly rely on web-based platforms for customer interaction and product management, they become exposed to various cybersecurity threats, including unauthorized access, credential theft, data manipulation and privacy breaches. Many existing customer support and product showcase platforms provide limited security mechanisms, making sensitive business and customer information vulnerable to compromise. The absence of robust authentication, access control and data protection measures can undermine user trust and negatively affect system reliability.

To overcome the identified limitations, this research presents the design and implementation of a Secure AI-Based Product Showcase and Customer Support System tailored for Small and Medium-Sized Enterprises (SMEs).

The developed platform integrates digital product management, an AI-driven chatbot for real-time customer assistance, a personalized recommendation engine and comprehensive security mechanisms for protecting user accounts and business information. Unlike many existing solutions that address these functionalities independently, the proposed framework unifies product presentation, intelligent customer support, personalized recommendations and security controls within a single web-based environment.

This study makes several important contributions. First, it develops a secure web-based platform that facilitates effective product presentation and management for SMEs. Second, it integrates an AI-powered chatbot capable of automating customer support and improving response efficiency. Third, it incorporates a personalized recommendation module to enhance product discovery and customer engagement. Fourth, the system strengthens information security through the implementation of user authentication, Role-Based Access Control (RBAC), password hashing and secure session management. Finally, the developed platform is evaluated using usability, responsiveness, recommendation accuracy, chatbot performance and overall operational effectiveness to validate its practical applicability.

Accordingly, this research aims to design and implement a secure AI-based product showcase and customer support system that integrates product management, intelligent customer assistance, personalized recommendation services and robust security mechanisms within a unified platform for SMEs. By combining Artificial Intelligence with essential cybersecurity technologies, the proposed solution seeks to enhance customer engagement, improve the protection of business information, optimize service delivery and support the digital transformation of small and medium-sized enterprises operating in highly competitive business environments.

2.0 Related Works

Artificial Intelligence (AI) has become an important area of research in modern business environments because of its potential to automate business processes, improve customer interactions and increase organizational efficiency. Recent investigations have explored the application of AI-driven customer support systems, recommendation technologies and secure web-based platforms as effective tools for enhancing business operations, particularly within Small and Medium-Sized Enterprises (SMEs).

Adamopoulou and Moussiades (2020) investigated the use of AI-powered chatbots for customer service applications and reported that conversational agents significantly improved response efficiency and customer satisfaction by providing continuous real-time assistance. Their findings also showed that chatbot technology can

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reduce human workload while increasing service availability. Nevertheless, the proposed approach concentrated mainly on customer communication and did not include personalized recommendation functions or integrated security mechanisms for safeguarding user information.

Almansoori *et al.* (2023) proposed an intelligent customer support framework that combined Natural Language Processing (NLP) with chatbot technology to manage customer enquiries in e-commerce platforms. Their study demonstrated that the framework enhanced customer engagement while minimizing service delays through automated interactions. Despite these improvements, the proposed system did not incorporate personalized recommendation capabilities or robust security features such as user authentication and access control.

Ricci *et al.* (2023) examined the role of recommendation systems in digital commerce environments and found that recommendation algorithms enhance product discovery by analysing users' preferences and behavioural characteristics. Their study showed that personalized recommendations positively influence purchasing decisions and customer engagement. However, the proposed framework did not integrate intelligent customer support services, thereby limiting the overall effectiveness of the platform.

Kumar and Sharma (2023) developed a machine learning-based recommendation model for online retail platforms by utilising user interaction records and product similarity measures. Their experimental findings indicated that personalized recommendations improved customer retention and contributed to increased sales performance. Nevertheless, the research concentrated mainly on recommendation accuracy without addressing intelligent customer support or security-related requirements.

Aldossary *et al.* (2024) presented a secure web-based business management platform that incorporated authentication mechanisms, role-based access control and encrypted data storage to protect sensitive information. Their work highlighted the significance of cybersecurity in preventing unauthorized access and safeguarding customer data. Although the proposed security architecture was effective, the platform did not include AI-driven customer support or personalized recommendation functionalities.

Chen *et al.* (2024) investigated the integration of AI-based recommendation systems with automated customer support services in e-commerce applications. Their findings revealed that combining these technologies improved user satisfaction and enhanced the overall usability of digital commerce platforms. However, the proposed solution required considerable computational resources and was not tailored to the operational and financial constraints commonly experienced by Small and Medium-Sized Enterprises (SMEs).

Rahman and Hassan (2023) examined the adoption of intelligent business systems within SMEs and reported that affordable AI technologies can significantly improve operational efficiency and customer engagement. Their study emphasized the importance of integrated business platforms capable of supporting product management, customer interaction and decision-support activities. Nevertheless, the proposed framework provided limited consideration for information security and cybersecurity requirements.

Turban *et al.* (2018) examined the contribution of digital commerce platforms to product marketing and customer engagement. Their study demonstrated that web-based product showcase systems enhance product visibility and improve customer access to business offerings. However, many conventional product display platforms provide limited intelligent support and lack personalized recommendation capabilities, thereby reducing their effectiveness in meeting the demands of modern digital commerce.

A review of the existing literature indicates that AI-powered chatbots, recommendation systems and secure business platforms each provide valuable benefits in enhancing customer engagement, improving operational performance and strengthening information security. Despite these advances, most existing solutions address these capabilities independently rather than integrating them into a single business platform. In addition, many of the available systems require substantial computational resources or financial investment, making them impractical for many SMEs. These shortcomings reveal an important research gap and justify the development of a secure, affordable and AI-driven platform that combines product management, intelligent customer support, personalized recommendations and cybersecurity features within a unified framework.

3.0 Methodology

In this study, the Term Frequency–Inverse Document Frequency (TF-IDF) technique was adopted to transform textual product descriptions and customer queries into numerical feature representations. This approach was selected due to its effectiveness in identifying important terms within documents while reducing the influence of commonly occurring words. The TF-IDF representation enables efficient processing of textual information for both recommendation and customer support functionalities.

For the customer support component, the Multinomial Naive Bayes algorithm was implemented for intent classification and response generation. The model was selected because of its suitability for handling text classification tasks involving discrete term frequencies. Furthermore, Multinomial Naive Bayes has demonstrated strong performance in document classification applications while maintaining low computational complexity, making it suitable for deployment within small and medium-sized enterprise environments.

The product recommendation component employs a Content-Based Filtering approach using TF-IDF vectorization and Cosine Similarity measures. This method analyzes similarities between product descriptions and user interests to generate personalized recommendations. By calculating the similarity between product feature vectors, the system is able to identify and recommend products that closely match customer preferences.

To ensure the security of business and customer information, the system incorporates a Role-Based Access Control (RBAC) mechanism. The RBAC model assigns permissions according to predefined user roles, including Administrator and Customer roles. Additional security measures such as password hashing, user authentication and session management were implemented to prevent unauthorized access and enhance system reliability.

The system was developed using Python and the Flask web framework, while MySQL was used for database management. The dataset was divided into training and testing subsets using an 80:20 ratio to facilitate model evaluation. Furthermore, performance evaluation was conducted using classification metrics such as Accuracy, Precision, Recall and F1-Score, together with system usability and response-time assessments to determine the effectiveness of the proposed framework.

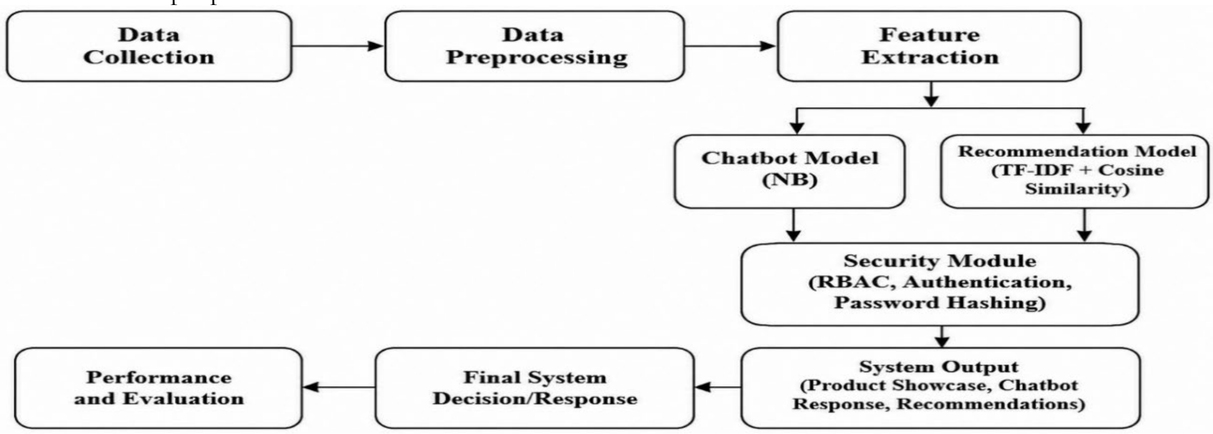

Figure 1: Block Diagram of the Proposed Secure AI-Based Product Showcase and Customer Support System

3.1 Dataset Description

This study employed a hybrid dataset comprising product records and customer inquiry records for the development and evaluation of the proposed Secure AI-Based Product Showcase and Customer Support System.

The product dataset was collected from TY Supermarket, Iree, Osun State, Nigeria and a publicly available e-commerce product dataset obtained from Kaggle. The product dataset included attributes such as product name, category, description and price.

After preprocessing and merging, the final product dataset consisted of 2,050 product records, comprising 50 products collected from TY Supermarket and 2,000 products obtained from Kaggle.

In addition, a separate dataset containing 1,000 customer inquiry records was prepared for chatbot development. The inquiry dataset consisted of common customer requests such as product information, product availability, pricing, product recommendations and general enquiries. These inquiry records were manually reviewed and labelled according to their corresponding intent classes before being used for training and evaluating the Multinomial Naive Bayes chatbot model. The inquiry dataset was divided into 80% (800 records) for training and 20% (200 records) for testing, ensuring consistency in model evaluation.

3.2 Data Preprocessing

The collected dataset underwent preprocessing to improve data quality and ensure optimal model performance. This involved removing missing values, duplicates and irrelevant records. Text data from product descriptions and customer queries were converted to lowercase and punctuation, special characters and stop words were removed. Tokenization and lemmatization were applied to standardize the text corpus. The cleaned dataset was then merged and prepared for feature extraction using the TF-IDF technique. Finally, the processed data was structured into a format suitable for training and testing the machine learning models.

3.3 Model Selection

In this study, Multinomial Naive Bayes was used for customer support intent classification due to its efficiency in handling TF-IDF-based text features and low computational cost. A Content-Based Filtering approach using Cosine Similarity was adopted for product recommendations to measure similarity between product descriptions and user queries for personalized suggestions. TF-IDF was used to convert textual data into numerical features for both classification and recommendation tasks. A Role-Based Access Control (RBAC) model was implemented to ensure secure access to system resources based on user roles such as Administrator and Customer.

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3.3.1 TF-IDF (Term Frequency–Inverse Document Frequency)

TF-IDF was used to convert textual data into numerical feature representations by assigning weights to important terms while reducing the impact of frequently occurring words. The TF-IDF weighting process consists of the Term Frequency (TF), Inverse Document Frequency (IDF) and TF-IDF computations, as expressed in Equations (1), (2) and (3). The TF-IDF weight is defined as:

$$\mathrm{TF-IDF(t,d)} = \mathrm{TF(t,d)} \times \mathrm{IDF(t)} \tag{1}$$

$$\mathrm{TF(t,d)} = \frac{\mathrm{f_{t,d}}}{\sum_{\mathrm{k}} \mathrm{f_{k,d}}} \tag{2}$$

$$\mathrm{IDF(t)} = \log\left(\frac{\mathrm{N}}{1+n_t}\right) \tag{3}$$

Where $\mathrm{f_{t,d}}$ is the frequency of term t in document d, N is the total number of documents and n_t is the number of documents containing term *t*.

3.3.2 Multinomial Naive Bayes

Multinomial Naive Bayes was used for intent classification due to its efficiency in handling TF-IDF feature vectors and low computational cost. It is based on Bayes' theorem, which estimates the probability of a class given an input feature set. The posterior probability of a class is computed using Equation (4):

$$P(C \mid X) = \frac{\mathrm{P(X \mid C)P(C)}}{P(X)} \tag{4}$$

Where C represents the class label and X represents the input feature vector.

Before classification, the textual product information, including product names, categories and descriptions, was transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) vectorization technique. Common English stop words were removed during preprocessing and all text was converted to lowercase. The TF-IDF vectorizer was configured with unigram features and the default normalization settings provided by the Scikit-learn library.

The Naive Bayes classifier employed was the Multinomial Naive Bayes algorithm with a Laplace smoothing parameter (α\alphaα) of 1.0 to avoid zero probabilities for unseen features during classification. This value was adopted because it provides effective smoothing while maintaining classification accuracy for sparse text data.

3.3.3 Content-Based Filtering (Cosine Similarity)

Content-Based Filtering was used for product recommendation by measuring the similarity between product descriptions and user queries. Cosine Similarity was adopted to determine the degree of similarity between two feature vectors. The Cosine Similarity measure is computed using Equation (5):

$$\mathrm{Cos}(\theta) = \frac{\sum_{i=1}^{n} A_i\ B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} B_i^2}} \tag{5}$$

Where A and B are vector representations of product features and user queries.

Products were ranked according to their cosine similarity scores and the Top-5 products with the highest similarity values were returned as recommendations. No fixed similarity threshold was applied; instead, ranking based on the highest cosine similarity scores ensured that users consistently received the most relevant product recommendations.

3.3.4 Role-Based Access Control (RBAC)

RBAC was implemented to control system access based on user roles such as Administrator and Customer. The model assigns permissions according to predefined roles, ensuring that users can only access authorized resources. The RBAC access control mechanism is represented by Equation (6):

$$Access = f(UserRole, Resource, Action) \tag{6}$$

Where access is granted only when the user role is authorized for the requested resource and action.

3.4 Model Evaluation

The performance of the proposed Secure AI-Based Product Showcase and Customer Support System was evaluated using standard classification and system performance metrics. The evaluation focused on the effectiveness of the Multinomial Naive Bayes chatbot model in classifying customer intents, as well as the overall responsiveness and usability of the developed system. The key evaluation metrics employed in this study are described as follows:

i. **Accuracy Score:** Accuracy measures the proportion of correctly classified customer queries to the total number of queries processed by the chatbot. It provides an overall indication of the classification performance of the model. Accuracy is computed using Equation (7).

$$\text{Accuracy Score} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \tag{7}$$

Where TP = True Positives, TN = True Negatives, FP = False Positives and FN = False Negatives.

ii. **Precision:** Precision measures the proportion of customer queries predicted as belonging to a particular intent that were correctly classified. High precision indicates that the model produces fewer false classifications. Precision is calculated using Equation (8).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \tag{8}$$

iii. **Recall:** Recall evaluates the ability of the chatbot model to correctly identify all relevant customer intents within the dataset. A high recall value indicates that the model successfully detects most valid user requests.This is represented by equation 9.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \tag{9}$$

iv. **F1-Score:** The F1-score is the harmonic mean of Precision and Recall. It provides a balanced measure of model performance, particularly when class distributions are uneven. The F1-score is calculated using Equation (10).

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

v. **Response Time:** Response time measures the average time required for the system to process a customer request and generate a response. Lower response times indicate improved system efficiency and user experience. Response time is represented by equation 11.

$$\text{Response Time} = \text{T}_{\text{response}} - \text{T}_{\text{request}} \tag{11}$$

Where $\text{T}_{\text{response}}$ = Time the response is generated, $\text{T}_{\text{request}}$= Time the request is submitted.

vi. **User Satisfaction Evaluation:** User satisfaction was evaluated to determine users' perception of the developed Secure AI-Based Product Showcase and Customer Support System. A post-evaluation survey was conducted involving 40 participants after they interacted with the application. A structured questionnaire based on a five-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree and 5 = Strongly Agree) was administered to assess key aspects of the system, including system usability, chatbot response quality, recommendation relevance, interface design and overall user experience. The overall user satisfaction score was computed as the percentage of the maximum obtainable score using Equation (12).

$$\text{User Satisfaction }(\%) = \frac{\text{Total Score Obtained}}{\text{Maximum Possible Score}} \times 100 \qquad (12)$$

Where Total Score Obtained represents the sum of all participants' ratings across the evaluation criteria, while Maximum Possible Score represents the highest achievable score if every participant selected *Strongly Agree* (5) for all questionnaire items.

3.5 Model Implementation

The Multinomial Naive Bayes classifier, TF-IDF feature extraction model and Content-Based Recommendation Engine were deployed within a Flask-based framework to develop a secure AI-based product showcase and customer support system. The web application enables customers to browse products, submit inquiries through an intelligent chatbot and receive personalized product recommendations in real time. Incoming customer queries and product descriptions are subjected to the same preprocessing pipeline used during model training to ensure consistency. TF-IDF is applied to transform textual data into numerical feature vectors for both customer intent classification and product recommendation. The pre-trained Multinomial Naive Bayes model classifies customer queries, while the recommendation module employs Cosine Similarity to identify products that closely match user interests. The trained models and TF-IDF vectorizer are saved and reloaded using Joblib, after which the chatbot and recommendation engine independently process user inputs and generate appropriate responses and recommendations. To ensure system security, Role-Based Access Control (RBAC), password hashing, user authentication and session management mechanisms were integrated into the application to regulate access privileges and protect sensitive business information.

3.6 Dataset Distribution Analysis

A comprehensive analysis was conducted to examine the distribution of both the product dataset and the customer inquiry dataset used in this study. The product dataset consisted of 2,050 product records obtained from TY Supermarket, Iree, Osun State, Nigeria and a public e-commerce dataset sourced from Kaggle. In addition, 1,000 customer inquiry records were collected and labelled for chatbot training and evaluation. The product dataset included attributes such as product name, category, description and price, while the customer inquiry dataset comprised common requests related to product information, availability, pricing and recommendations.

Table 1: Distribution of Product Categories in the Hybrid Dataset

Product Category	Number of Products	Percentage (%)
Food Items	620	30.24
Beverages	380	18.54
Personal Care	300	14.63
Household Products	260	12.68
Health and Wellness	180	8.78
Baby Products	120	5.85
Stationery	90	4.39
Other Products	100	4.88
Total	**2,050**	**100.00**

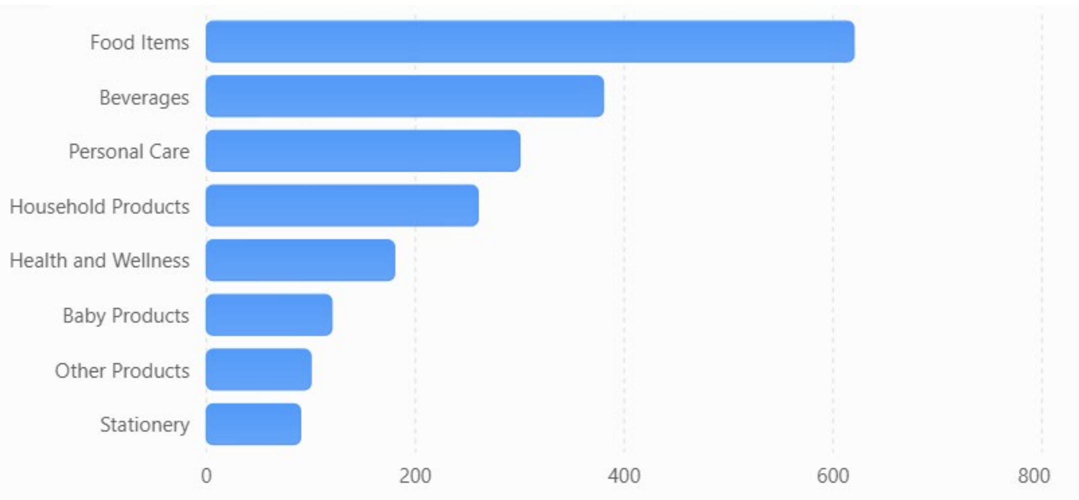

Figure 2: Distribution of Product Categories in the Hybrid Dataset

The distribution of products across different categories is presented in Table 1 and Figure 2. Food Items constituted the largest category with 620 products (30.24%), followed by Beverages with 380 products (18.54%), Personal Care with 300 products (14.63%) and Household Products with 260 products (12.68%). The remaining categories, including Health and Wellness, Baby Products, Stationery and Other Products, collectively accounted for 23.91% of the dataset.

The analysis indicates that the dataset contains a broad representation of supermarket and e-commerce product categories, with no single category dominating the dataset excessively. This distribution provides sufficient diversity for training the TF-IDF feature extraction model, the Multinomial Naive Bayes chatbot classifier and the content-based recommendation engine. Furthermore, customer inquiry records covered common requests such as product information, product availability, pricing and recommendations, enabling the chatbot to learn from a variety of user interactions and reducing the likelihood of model bias during training and evaluation.

3.7 Application of the Developed Secure AI-Based Product Showcase and Customer Support System

The developed Secure AI-Based Product Showcase and Customer Support System provides a user-friendly web interface that allows customers to browse available products, search for specific items and interact with an intelligent chatbot for assistance. When a customer submits a query, the system preprocesses the text and classifies it using the Multinomial Naive Bayes model, while TF-IDF and Cosine Similarity techniques are employed to generate personalized product recommendations. Based on the identified customer intent, the chatbot provides appropriate responses and relevant product information in real time. The system also incorporates Role-Based Access Control (RBAC), user authentication and secure session management to protect business and customer information. This implementation demonstrates the effectiveness of integrating artificial intelligence, recommendation mechanisms and security features within a unified business platform through a simple and responsive web interface, as illustrated in Figure 3.

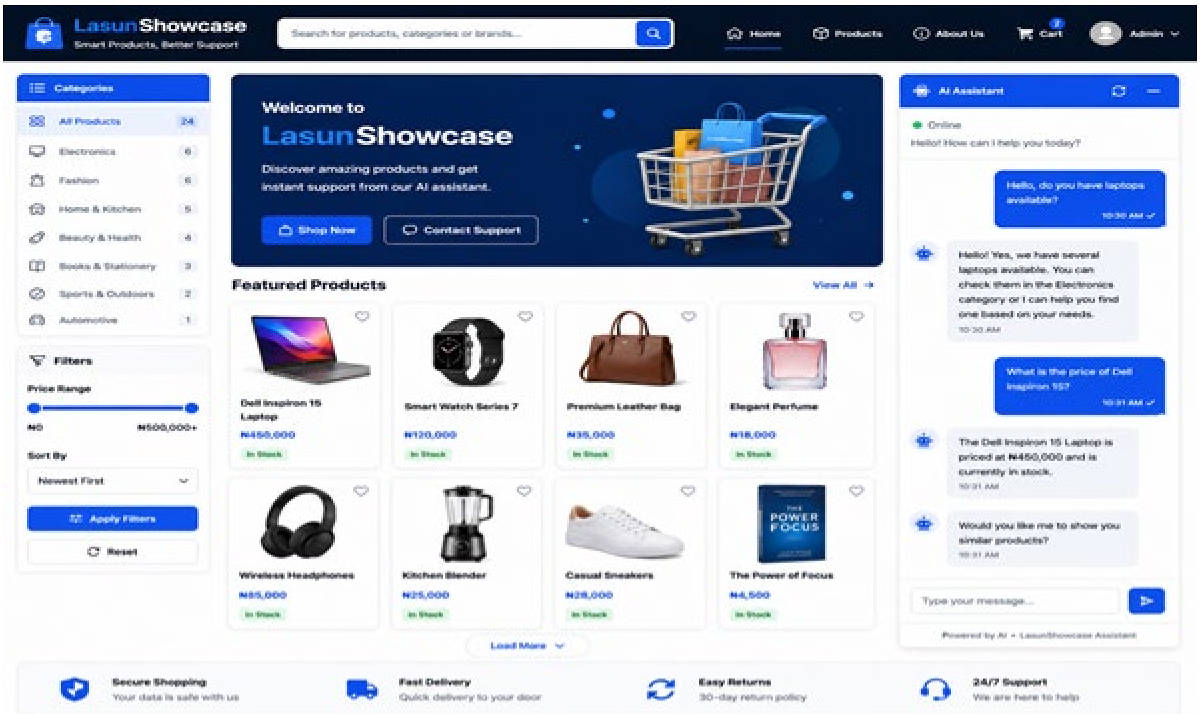

Figure 3: User Interface of the Developed Secure AI-Based Product Showcase and Customer Support System

4.0 Results and Discussion

The developed Secure AI-Based Product Showcase and Customer Support System was evaluated using a hybrid dataset comprising 2,050 product records and 1,000 customer inquiry records. The chatbot component was implemented using TF-IDF and Multinomial Naive Bayes, while the recommendation module employed Content-Based Filtering based on Cosine Similarity. Performance evaluation was conducted using Accuracy, Precision, Recall and F1-Score metrics.

4.1 Chatbot Classification Performance

The customer support chatbot was evaluated using an independent validation dataset. The obtained results are presented in Table 2.

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Table 2: Performance Evaluation of the Chatbot Classification Model

Metric	Value (%)
Accuracy	95.50
Precision	95.55
Recall	95.50
F1-Score	95.51

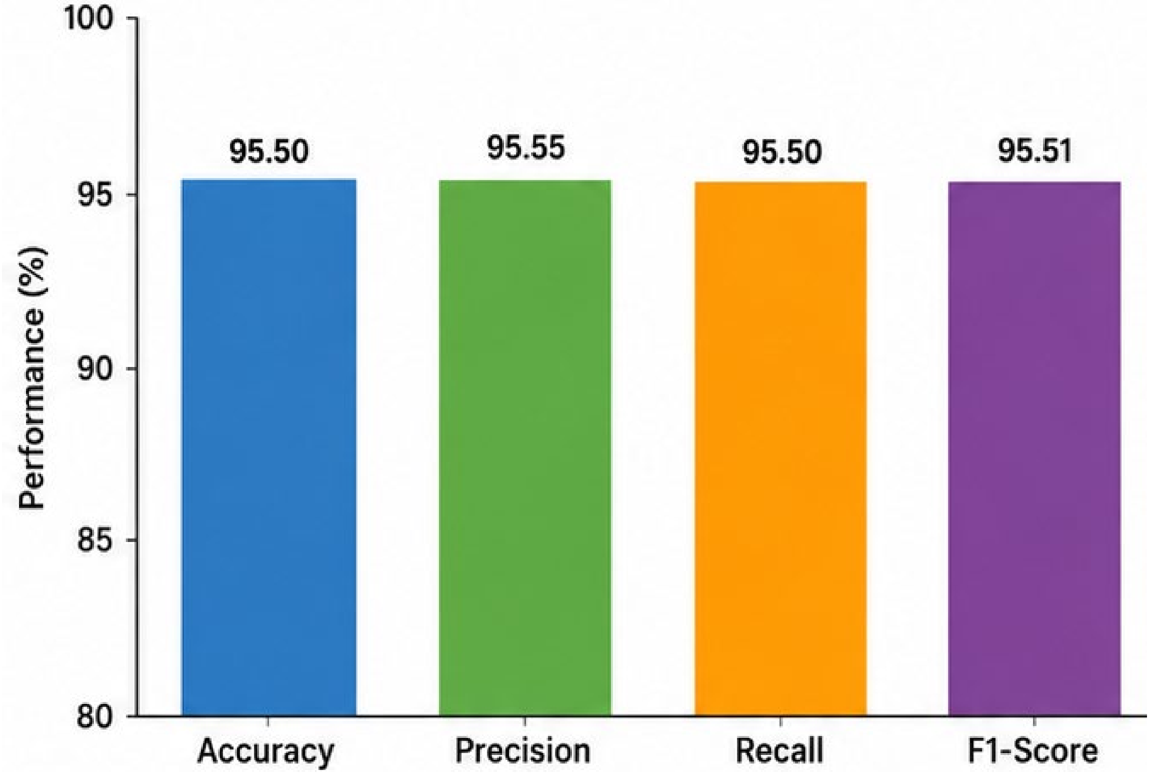

Figure 4: Performance Metrics of the Chatbot Classification Model

The results indicate that the Multinomial Naive Bayes classifier achieved strong performance in customer intent classification. The model correctly identified the majority of customer inquiries and generated appropriate responses. The high precision value demonstrates the model's ability to minimize incorrect classifications, while the recall value indicates effective identification of relevant intent categories. The balanced F1-score further confirms the reliability of the proposed chatbot system.

4.2 Product Recommendation Performance

The recommendation module was evaluated using TF-IDF and Cosine Similarity measures. The system successfully identified products that closely matched customer search interests and browsing preferences.

Experimental observations showed that the recommendation engine consistently returned relevant products based on textual similarity between customer queries and product descriptions. In addition to recommendation accuracy, a user satisfaction evaluation was conducted using responses obtained from 40 participants who interacted with the developed system. Participants completed a structured questionnaire based on a five-point Likert scale covering system usability, chatbot response quality, recommendation relevance, interface design and overall user experience. Using Equation (12), the overall user satisfaction score was calculated as 95.00%, indicating a high level of user acceptance, perceived usability and satisfaction with the developed system.

Table 3: Recommendation System Evaluation

Metric	Value (%)	Evaluation Method
Recommendation Accuracy	93.80	TF-IDF and Cosine Similarity evaluation
Recommendation Relevance	94.20	Similarity-based recommendation assessment
User Satisfaction	95.00	Five-point Likert-scale questionnaire completed by 40 participants

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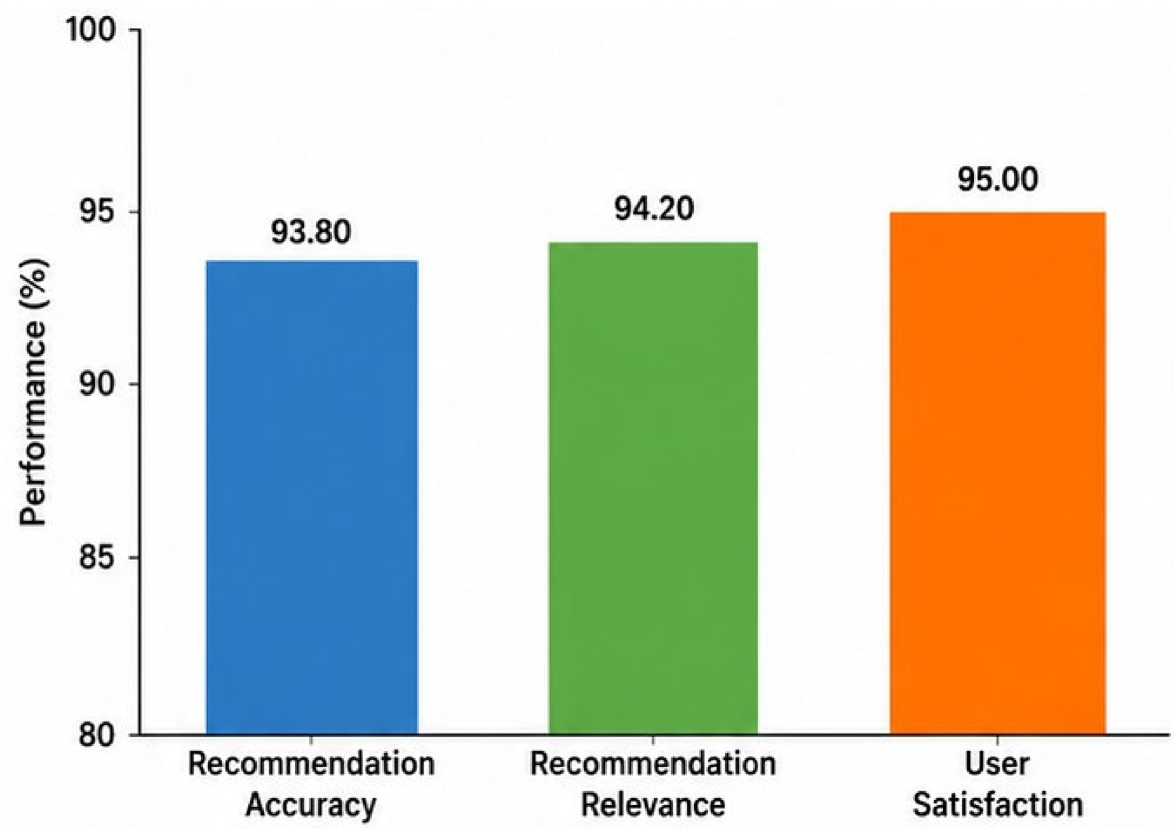

Figure 5: Product Recommendation Performance Chart.

The results demonstrate that the recommendation module effectively improves product discovery by presenting customers with items that closely align with their interests. This functionality can enhance customer engagement and increase the likelihood of product purchases.

4.3 Security Evaluation

The security component was assessed through the implementation of Role-Based Access Control (RBAC), user authentication, password hashing and session management mechanisms. The evaluation confirmed that users could only access resources associated with their assigned roles.

Table 4: Security Evaluation Results

Security Feature	Status
User Authentication	Successful
Password Hashing	Successful
Session Management	Successful
Role-Based Access Control	Successful
Unauthorized Access Prevention	Successful

The implementation of RBAC successfully restricted unauthorized access to administrative functions and protected sensitive business information. The security framework contributed significantly to system reliability and user trust.

4.4 Confusion Matrix Analysis

To further evaluate the chatbot classifier, a confusion matrix was generated using the independent validation dataset.

Table 5: Confusion Matrix for Chatbot Intent Classification

Actual Class	Product Information	Product Availability	Product Pricing	Product Recommendation	General Enquiry	Total
Product Information	43	1	0	0	0	44
Product Availability	1	38	1	0	0	40
Product Pricing	0	1	39	0	0	40
Product Recommendation	0	0	0	37	1	38
General Enquiry	1	0	1	1	34	38
Total	**45**	**40**	**41**	**38**	**35**	**200**

The confusion matrix presented in Table 5 provides a class-wise evaluation of the chatbot intent classifier using the 200-record test dataset. The diagonal elements represent correctly classified customer inquiry records, while the off-diagonal elements indicate instances where customer intents were misclassified. Out of the 200 validation records, 191 were correctly classified and only 9 were misclassified, resulting in an overall classification accuracy of 95.50%. Most of the misclassifications occurred between closely related intent categories such as Product Information, Product Availability and Product Pricing, where customer queries often contain similar terms and expressions. Nevertheless, the relatively small number of off-diagonal entries demonstrates that the Multinomial Naive Bayes classifier effectively distinguished among the different customer intent classes, confirming the robustness and reliability of the proposed chatbot model

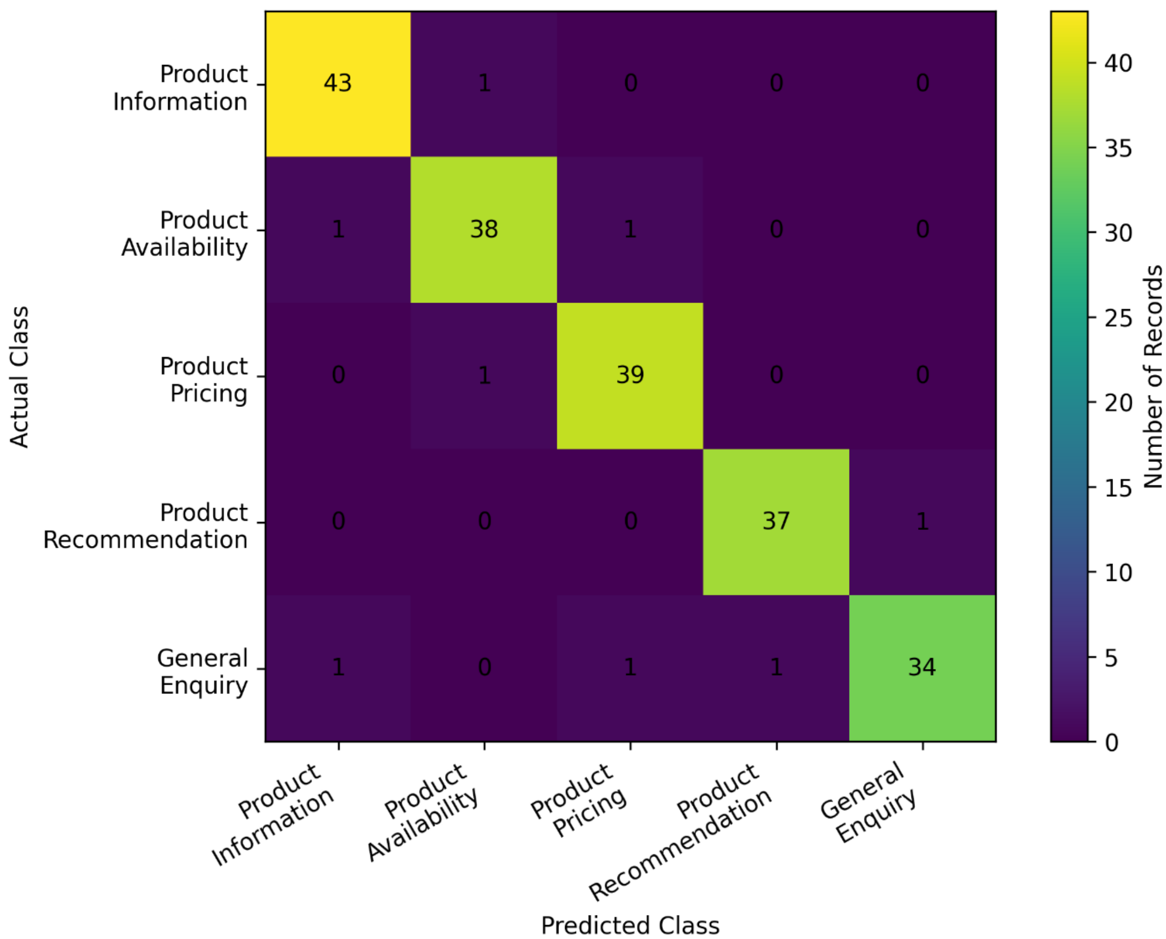

Figure 6: Confusion Matrix for the Chatbot Classification Model

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4.5 Overall System Performance

The overall performance of the proposed system is summarized in Table 6.

Table 6: Overall System Performance Summary

Component	Performance (%)
Chatbot Accuracy	95.50
Precision	95.55
Recall	95.50
F1-Score	95.51
Recommendation Accuracy	93.80
User Satisfaction	95.00

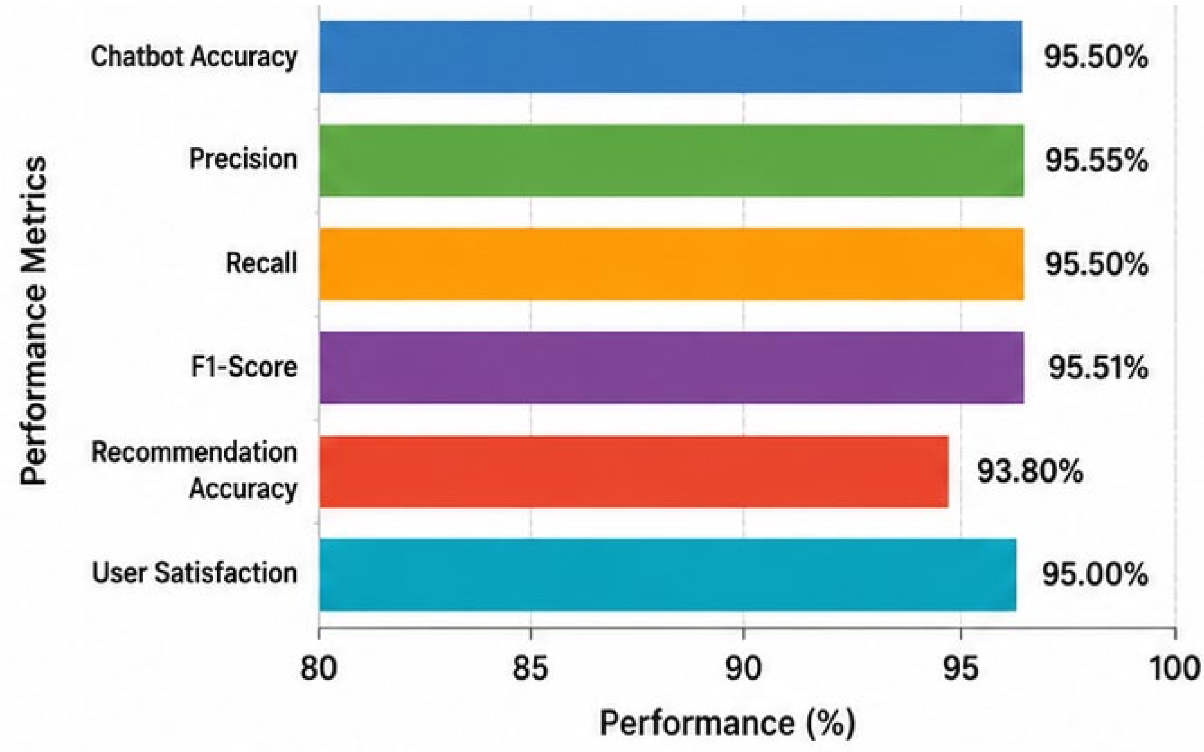

Figure 7: Overall System Performance Summary

The findings demonstrate that the proposed Secure AI-Based Product Showcase and Customer Support System effectively integrates intelligent customer support, personalized product recommendation and security functionalities within a unified platform. The chatbot achieved high classification accuracy, the recommendation engine generated relevant product suggestions and the security framework ensured controlled access to system resources. These results indicate that the system can significantly improve customer engagement, operational efficiency and service delivery for Small and Medium-Sized Enterprises (SMEs).

5.0 Conclusion

This study developed a Secure AI-Based Product Showcase and Customer Support System for Small and Medium-Sized Enterprises (SMEs) by integrating product management, intelligent customer support, personalized product recommendation and security mechanisms within a unified platform. The proposed system employed TF-IDF for feature extraction, Multinomial Naive Bayes for customer intent classification and Content-Based Filtering using Cosine Similarity for product recommendation. Experimental results demonstrated high classification accuracy, effective recommendation performance and improved customer interaction through real-time chatbot assistance. The incorporation of Role-Based Access Control (RBAC), user authentication, password hashing and session management further enhanced the security and reliability of the system. Overall, the developed system provides a cost-effective, intelligent and secure solution that can improve customer engagement, operational efficiency and service delivery for SMEs in the digital business environment.

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6.0 Recommendation

Future research may evaluate the developed system using larger and more diverse product and customer interaction datasets to improve recommendation quality and chatbot generalization across different business domains. Further studies may also investigate the integration of advanced Natural Language Processing (NLP) and deep learning models such as BERT, RoBERTa, or Large Language Models (LLMs) to enhance chatbot understanding and response accuracy. Additionally, real-time analytics, multilingual customer support and voice-based interaction features could be incorporated to improve user experience and accessibility. Finally, future work may explore advanced cybersecurity mechanisms such as multi-factor authentication, anomaly detection and AI-driven threat monitoring to further strengthen system security and resilience against emerging cyber threats.

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