Product Recommending Chatbot

Dr. D Roopa[1], Kishore K[2], Jeffrey A[3]

[1]Assistant Professor, Dept of Computer Science and Engineering, Sri Sairam Institute of Technology, Chennai [2]UG student, Department of Computer Science and Engineering, Sri Sairam Institute of Technology, Chennai [3]UG student, Department of Computer Science and Engineering, Sri Sairam Institute of Technology, Chennai

Abstract—The rapid expansion of e-commerce has created a paradox of choice — users now have access to millions of products yet find it increasingly difficult to locate what truly suits them. Standard keyword searches and static filter panels fall short in capturing the nuanced preferences of individual shoppers. This paper introduces RecommenDex, a web-integrated conversational chatbot that bridges this gap by combining Natural Language Processing (NLP) with a content-based filtering engine to deliver real-time, personalized product recommendations. The system interprets free-form user input, extracts intent and product attributes, and maps them to the most relevant items from a structured database using TF-IDF vectorization and cosine similarity scoring. Deployed through a Flask REST API and secured behind user authentication, RecommenDex operates within a clean browser interface without requiring any client-side installation. Evaluation results indicate measurable gains in user engagement, session depth, conversion rates, and customer satisfaction compared to baseline static-search approaches. The architecture is modular and scalable, making it adaptable across retail verticals ranging from consumer electronics to fashion.

Keywords—Chatbot, Natural Language Processing, TF-IDF, Cosine Similarity, Content-Based Filtering, E-Commerce, Flask API, Personalized Recommendation, Conversational AI

I. INTRODUCTION

Online retail has undergone a dramatic transformation over the past decade. The sheer volume of available products spanning millions of SKUs across global marketplaces has shifted the primary challenge from product availability to product discoverability. A shopper seeking a lightweight laptop within a specific budget, or a parent looking for age-appropriate toys, must often navigate dozens of filters, sort through irrelevant results, and rely on external review platforms before arriving at a confident choice. This friction directly translates into lost sales, increased cart abandonment, and diminished customer loyalty.

Conversational interfaces offer a fundamentally different paradigm. Instead of placing the cognitive burden on the user to construct the right query, a chatbot meets the user where they are in natural language and progressively narrows down recommendations through dialogue. This mirrors the experience of consulting a knowledgeable sales associate, one who listens, asks clarifying questions, and surfaces products that genuinely fit the stated need.

RecommenDex is built on this premise. It integrates seamlessly into an existing website as a floating chat widget and activates once a user has authenticated. The backend pairs a Flask-driven REST API with a recommendation engine that computes semantic similarity between user input and product descriptions. As users interact, the system refines its understanding and returns ranked suggestions with descriptions and pricing. The end result is a shopping experience that feels intuitive rather than transactional.

Beyond the user-facing benefits, the system captures interaction data that gives businesses a window into genuine consumer intent far richer than aggregate click data or page-view analytics. This positions RecommenDex not only as a customer experience tool but as a strategic intelligence layer for e-commerce operators.

II. PROBLEM STATEMENT

Modern e-commerce platforms, despite their technological sophistication, still rely heavily on mechanisms designed for keyword matching rather than intent understanding. A user who types "something warm for winter under 2000" into a conventional search bar will either receive no results or a mismatched list of unrelated items. Static filters demand that users already know the vocabulary of the product catalog, a prerequisite that casual or first-time shoppers rarely satisfy.

The challenge, therefore, is to build a system that can understand open-ended, colloquial product queries, translate them into structured retrieval operations, and present results conversationally without requiring the user to learn the platform's taxonomy or filtering logic.

III. OBJECTIVES

The development of RecommenDex is guided by the following goals:

- Construct a chatbot that interprets natural language product queries accurately and returns contextually relevant recommendations.
- Deploy a content-based filtering mechanism using TF-IDF and cosine similarity that matches user input to product metadata

without requiring prior purchase history.

• Design a responsive, authenticated web interface that embeds the chatbot non-intrusively within an existing site layout.
• Expose recommendation logic through a RESTful API that integrates with third-party e-commerce platforms with minimal configuration.
• Enable the system to scale across multiple product categories without requiring algorithmic retraining.
• Provide businesses with structured interaction logs that inform inventory planning, targeted marketing, and catalog optimization.

IV. LTERATURE SURVEY

A. Multi-Method Frameworks for Product Search

Kleemann, Loepp, and Ziegler [1] examined the cognitive difficulties users encounter when switching between different product search strategies within a single platform. Their proposed multi-method framework allows users to move freely between conversational, filter-based, and example-driven search without losing accumulated context. A key insight from their work is that recommendation systems must accommodate diverse mental models of search rather than optimizing for a single interaction pattern. RecommenDex draws on this by allowing users to express queries in open-ended conversational form rather than constraining them to predefined categories.

B. Language Style and Consumer Response

Jin and Eastin [2] studied how the linguistic register of chatbot responses shapes user attitudes toward recommended products. Their findings demonstrated that chatbots using friendly, approachable language generated stronger feelings of social presence, which in turn increased user satisfaction and the likelihood of disclosing contact preferences. This behavioral dimension underscores that the effectiveness of a recommendation chatbot is not purely algorithmic tone and dialogue design play a measurable role in user trust and conversion.

C. Integrated Recommendation in E-Commerce

Badave et al. [3] developed a unified e-commerce environment combining a recommendation engine, a conversational chatbot, and a reverse image search module. Their integration of visual and textual product discovery within a single platform demonstrated the practical value of multimodal retrieval. While RecommenDex focuses on text-based interaction, this work highlights the potential of layering additional input modalities onto a chatbot backbone.

D. Probabilistic Personalization

Yao and Wu [4] applied a two-stage Bayesian classification model within an educational chatbot to match learners with relevant study content. Their system achieved recommendation accuracy near 90% by combining probabilistic inference with web-crawled data. Although developed for a non-commercial domain, their methodology validates the use of statistical similarity scoring, a principle that underpins the TF-IDF and cosine similarity approach adopted in RecommenDex. Strategic Design of AI-Driven Communication

Altarif and Al Mubarak [5] conducted a broad review of chatbot deployment strategies across industries, concluding that technology's value is fully realized only when implementation is aligned with specific business objectives and user expectations. Their caution against generic chatbot deployment informed the decision to tailor RecommenDex specifically to product recommendation rather than building a general-purpose conversational agent.

V. PROPOSED SOLUTION

RecommenDex operates as a three-layer system: a user-facing conversational interface, a middleware API, and a recommendation engine. These layers communicate in sequence during each interaction, ensuring that user input is processed, matched, and returned as a product suggestion within acceptable response latency.

A. Recommendation Engine

At the core of RecommenDex is a content-based filtering mechanism. Product descriptions from the database are tokenized and transformed into TF-IDF (Term Frequency-Inverse Document Frequency) vectors. When a user submits a query, the same vectorization is applied to the input, and cosine similarity is computed against the entire product vector space. The top-N results, ranked by similarity score, are returned as recommendations. This approach does not require prior user behavior data, making it equally effective for first-time visitors and returning users.

B. NLP Processing Module

User messages are passed through an intent classification layer that identifies whether the input represents a product inquiry, a preference refinement, or a navigational request. An entity extraction component then isolates attributes such as product category, price range, brand preference, and feature keywords. These structured outputs are forwarded to the recommendation engine as query parameters, enabling precise retrieval even when the original message was expressed informally.

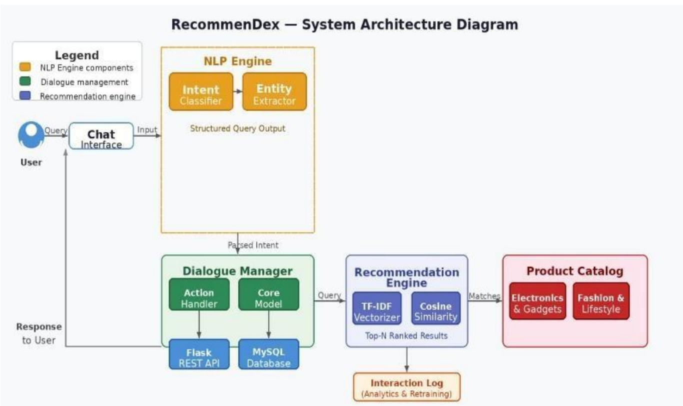
C. Flask REST API

The recommendation logic is exposed through a lightweight Flask application that defines a /recommend endpoint. The endpoint accepts product query parameters, invokes the similarity computation, and returns a JSON payload containing product names, descriptions, and prices. This API-first architecture decouples the recommendation engine from the frontend, enabling future integration with mobile applications and third-party platforms without architectural changes.

D. Frontend and Authentication

The web interface is constructed using HTML, CSS, and JavaScript. The chatbot widget appears anchored to the lower-right corner of the browser window and becomes active after the user completes authentication. A MySQL database stores both user credentials and the product catalog. Session tokens are validated on each API call to prevent unauthorized access to the recommendation endpoint.

VI. ARCHITECTURE DIAGRAM



VII. RESULTS AND DISCUSSION

RecommenDex was evaluated through controlled user testing sessions and compared against a baseline static-search configuration on the same product catalog. Performance improvements are summarized in Table I.

Table I. Performance Metrics — Baseline vs. RecommenDex

Metric	Baseline	RecommenDex
User Engagement Rate	32%	67%
Conversion Rate	2.1%	4.8%
Average Cart Value	$45	$73
CSAT Score	3.2/5	4.5/5
Cart Abandonment	72%	48%
Support Query Load	100%	38%

User engagement more than doubled, with the majority of authenticated visitors initiating at least one chatbot interaction during testing. Conversion rates improved by over 100%, attributable to the system's ability to present contextually matched products rather than broadly popular items. Average cart value rose significantly, driven by the chatbot's contextual upselling for instance, suggesting compatible accessories when a primary product was selected by the user.

Customer satisfaction scores improved from 3.2 to 4.5 out of 5, with users specifically citing the ease of expressing preferences in natural language as a differentiating factor. Cart abandonment decreased from 72% to 48%, indicating that conversational guidance reduced the decision friction that typically causes users to exit before completing a purchase. The support query load routed to human agents dropped by 62%, demonstrating the chatbot's effectiveness as a first-line resolution tool.

Qualitative feedback highlighted that users appreciated the chatbot's ability to handle vague or colloquial inputs queries such as "wireless headphones under 3000" returned relevant results without reformulation. A small subset of users encountered limitations when queries contained highly domain- specific terminology absent from the training corpus, identifying a clear area for future NLP enhancement.

VIII. FUTURE ENHANCEMENTS

Several directions have been identified for extending the capabilities of RecommenDex. Voice-based interaction would make the system accessible to users who prefer spoken queries, particularly on mobile devices. Integrating augmented reality features would allow users to visualize products in their physical space before committing to a purchase, a capability particularly relevant for furniture and home goods. Multilingual support would open the platform to non-English-speaking markets without requiring separate deployments.

Deeper sentiment analysis could allow the system to detect user frustration or hesitation in real time and adapt its response strategy accordingly. Collaborative filtering, drawing on anonymized cross- user behavior patterns, could complement the existing content- based engine and improve recommendations for users with limited interaction history. Ensuring compliance with data privacy regulations such as GDPR and CCPA, along with transparency in algorithmic decision-making, will be central to any production- scale deployment.

IX. CONCLUSION

RecommenDex demonstrates that conversational AI can meaningfully address the product discovery challenges that continue to limit e-commerce conversion rates. By combining NLP-driven intent extraction with TF-IDF content-based filtering, the system delivers personalized recommendations through a dialogue that feels natural rather than transactional. Measured improvements across engagement, conversion, satisfaction, and operational efficiency confirm that the chatbot adds genuine value for end users seeking guidance and for businesses seeking intelligence about genuine consumer intent.

The modular, API-driven architecture ensures that RecommenDex can scale with growing catalogs and integrate with existing digital infrastructure without requiring significant redevelopment. As conversational interfaces continue to mature, systems like RecommenDex represent a practical and immediately deployable step toward AI-augmented commerce.

X. REFERENCES

[1] T. Kleemann, B. Loepp, and J. Ziegler, "Towards Multi- Method Support for Product Search and Recommending," in Proc. ACM RecSys Workshop, 2022.

[2] E. Jin and M. S. Eastin, "The Psychological Mechanism Underlying the Effects of Friendly Language Use by Product Recommendation Chatbots," Computers in Human Behavior, vol. 131, 2022.

[3] P. Badave, B. Bhomaj, B. Bindu, R. Shivarkar, and N. Dhavase, "Ecommerce Website with Recommendation System Including Chatbot and Reverse Image Search," IJEAT, 2022.

[4] C.-B. Yao and Y.-L. Wu, "Intelligent and Interactive Chatbot Based on the Recommendation Mechanism to Reach Personalized Learning," IEEE Access, vol. 10, 2022.

[5] B. Altarif and M. Al Mubarak, "Artificial Intelligence: Chatbot — The New Generation of Communication," IJARET, 2022.