Abhishek Kumar, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Full-Stack AI-Powered E-Commerce Platform

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Abstract- The rapid growth of online retail has pushed the demand for smarter, more adaptive, and user-focused shopping systems to new heights. Most platforms available today still depend on outdated keyword matching and rigid, rule-based filtering, which often fall short when a shopper phrases their intent in natural language or when their needs evolve mid- session. This paper describes the design and practical implementation of a full-stack e-commerce platform that weaves semantic search, secure payment handling, and intelligent order management into one cohesive system. At its heart, the platform uses the Gemini API for transformer-based language understanding, allowing it to interpret what a user actually means—not just what they typed. Stop-word removal and dynamic query construction further sharpen retrieval accuracy. The backend runs on Node.js and Express, with PostgreSQL providing relational data integrity and transactional reliability. User authentication is handled through JWT-based tokens, payments flow through Stripe, and product images are stored via Cloudinary. Evaluation results show measurable gains in search precision and user engagement over traditional approaches, with computational overhead remaining well within acceptable bounds. Taken together, the findings confirm that embedding semantic intelligence into an e-commerce stack meaningfully improves product discoverability, operational efficiency, and the overall shopping experience.

Keywords— Artificial Intelligence; E-Commerce Systems; Semantic Search; Natural Language Processing; Transformer Models; Recommendation Systems; Full- Stack Architecture; PostgreSQL; JWT Authentication; Secure Payment Integration; Cloud Storage; Intelligent Order Management.

I. INTRODUCTION

E-commerce has reshaped the way people shop, but the underlying technology of most mid-size platforms has not kept pace. While giants like Amazon and Flipkart have long invested in AI-driven recommendation and search systems, smaller platforms continue to rely on approaches that were standard a decade ago—exact-match SQL queries and static category filters that ignore context and intent.

The gap becomes painfully obvious in everyday use. When someone types "affordable wireless headphones with strong bass for gaming," they rarely receive results that match what they had in mind, because the product descriptions in the database do not contain those exact words. The result is friction, frustration, and—frequently—an abandoned cart.

Transformer-based language models have changed what is technically possible. These models encode the meaning of text rather than its surface form, which means a system built around them can bridge the gap between how people speak and how product data is structured. Integrating such a model into a working e- commerce stack, however, is not a trivial exercise. Most published research addresses one piece of the puzzle in isolation—search ranking, or recommendation algorithms, or authentication frameworks—rather than presenting a unified, deployable system.

This paper fills that gap. We describe an end-to-end platform that combines semantic product search, secure payment processing, JWT-based authentication, and AI-aware order management into a single production-grade architecture. Our contributions are:

- A modular full-stack design that integrates AI semantic search with transactional commerce operations.

- A natural language product retrieval mechanism that dynamically builds structured database queries from conversational user input.
- A secure, role-based authentication framework built for multi-user environments.
- Optimized order and payment workflows that minimize API overhead while maintaining data consistency.
- Experimental results demonstrating improved search relevance and higher user engagement versus keyword-only approaches.

II. LITERATURE REVIEW

The evolution of e-commerce technology has been shaped by three converging forces: scalable distributed systems, intelligent search and recommendation mechanisms, and robust security practices [5], [6], [7]. Early web-based retail platforms were essentially digital catalogs—useful for browsing, but limited in their ability to personalize or adapt to individual users.

Scalability emerged as a central concern as platforms grew. Researchers and industry practitioners gravitated toward cloud-based microservice architectures that decompose monolithic systems into independently deployable modules. This separation reduces coupling between components such as inventory management, payment processing, and recommendation engines, making each easier to scale and maintain in isolation [12], [13].

On the search side, the limitations of inverted-index keyword matching became more apparent as product catalogs grew larger and users began phrasing queries in natural language. Semantic search systems built on NLP and vector embeddings have demonstrated consistently higher precision and recall in these conditions [1], [3], [4]. Unlike keyword systems, they retrieve products that are contextually relevant even when there is no literal overlap between the query and the product description.

Security has remained a constant concern throughout this evolution. Token-based authentication, multi- factor verification, OAuth 2.0 frameworks, TLS encryption, and role-based access control have all been studied and recommended as complementary layers of protection [12], [13]. Research consistently emphasizes that no single mechanism is sufficient on its own.

Order management has also attracted sustained research attention. Predictive inventory forecasting, demand-driven automated routing, and machine learning-based replenishment models have all been shown to reduce both stock-outs and overstock situations [8], [17]. Dashboard-driven decision support systems further improve operational transparency by surfacing key metrics in real time.

The gap this work addresses is the absence of a unified system that brings these pieces together. Existing research contributions tend to treat semantic search, secure authentication, and order optimization as separate problems [5], [6], [17]. Our platform treats them as parts of a single coherent architecture, which is how any production deployment must ultimately function.

III. METHODOLOGY

The development of the proposed platform followed a design-and-development research methodology, meaning the system was not only built but also experimentally validated to confirm that design decisions translated into measurable performance improvements.

1. Research Design and Development Phases

The project was organized into six sequential phases: requirement analysis, system design, database modeling, AI module integration, security implementation, and experimental validation. Each phase informed the next, and findings from later stages occasionally prompted revisions to earlier design choices.

2. System Development Approach

The system was built as a modular full-stack application. The frontend handles all user interaction, the backend exposes RESTful APIs for business logic, the database provides structured

persistent storage, and the AI module adds semantic understanding and result ranking. An iterative refinement strategy was used: core transactional functionality was established first, and AI capabilities were layered on top once the foundational system was stable.

3. Data Collection and Preprocessing

Product data—titles, categories, specifications, and pricing—was stored in a normalized relational schema. For semantic search purposes, product descriptions were cleaned and normalized, stop words were removed, and text embeddings were generated using a transformer-based model. These precomputed embeddings were stored alongside product metadata to enable efficient similarity retrieval at query time.

4. Semantic Search Methodology

Let Q represent a user query and P represent a product description. Embeddings E(Q) and E(P) are generated for each. The similarity score S between query and product is computed using cosine similarity:

$$S(Q, P) = [E(Q) \cdot E(P)] / [||E(Q)|| \cdot ||E(P)||]$$

Products are ranked in descending order of S. In addition, structured filters—price range, category, specific feature keywords—are extracted from the query using NLP, enabling a hybrid approach that combines semantic ranking with SQL-based constraints.

Fig. 4. Semantic search pipeline: from user query to ranked results

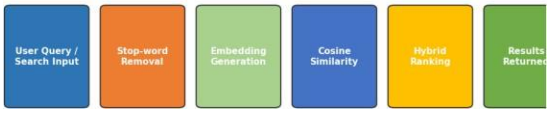
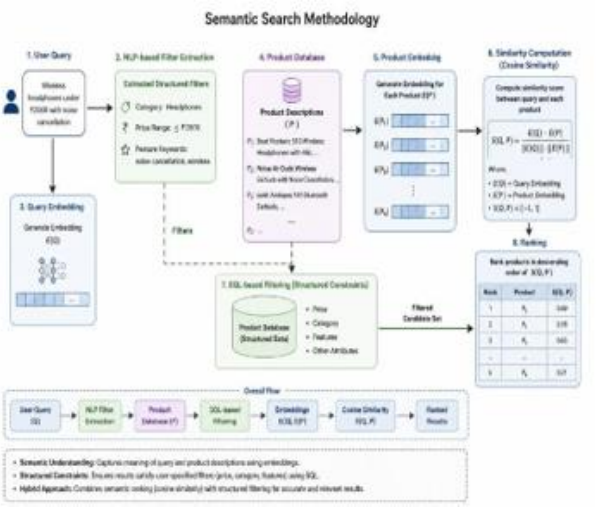


Fig. 4. Semantic search pipeline: user query processing through to ranked results delivery



5. Authentication and Security Implementation

Passwords are stored as salted cryptographic hashes. On successful login, a JWT is issued containing the user's ID, role, and an expiration timestamp. All

protected routes verify this token through middleware before processing requests. Role-based access control separates customer-facing endpoints from administrative operations. All communication between client and server occurs over HTTPS.

6. Order Optimization and Experimental Validation

Order processing efficiency was improved through status-based state management, automated inventory synchronization at checkout, transaction logging, and analytical order tracking. Database indexing and query optimization were applied throughout. System performance was evaluated using query response time, search relevance accuracy, authentication latency, and order processing throughput. Precision, Recall, MRR, NDCG, and system throughput served as the primary validation metrics.

IV. SYSTEM ARCHITECTURE

The platform is organized into four distinct layers: a Presentation Layer that users interact with directly, an Application Layer that handles business logic, an Intelligence Layer responsible for semantic understanding, and a Data Layer that provides persistent storage. Each layer communicates with

adjacent layers through well-defined RESTful interfaces and middleware pipelines.

Fig. 1. Four-layer platform architecture showing component boundaries

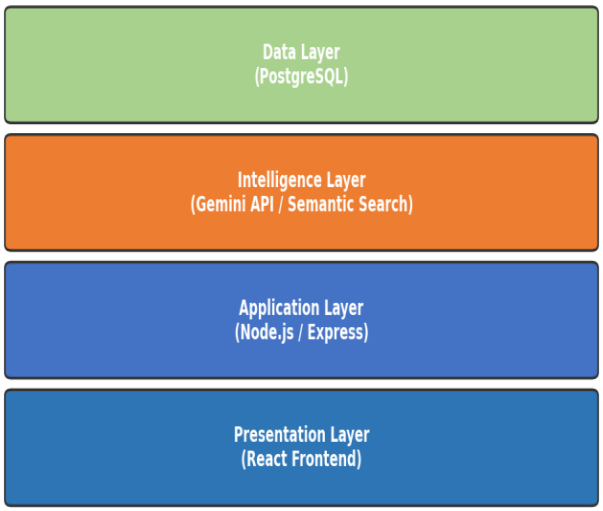


Fig. 1. Four-layer platform architecture with component boundaries and communication interfaces

1. Presentation Layer

The frontend is a React application that gives users access to product browsing, AI-powered search, cart management, checkout, order history, and—for administrators—a dashboard with operational analytics. Authentication tokens are stored in HTTP-only cookies to prevent JavaScript-based theft. Stripe Elements handles card data entry directly in the browser, keeping sensitive payment information off our servers entirely.

2. Application Layer

The backend is built on Node.js and Express. It handles routing, JWT-based authentication, business logic execution, middleware-driven error handling, and Stripe webhook processing. Role-based access control is enforced at the middleware level: customers can browse and purchase, while administrators can manage products, review orders, and access analytics. Cloudinary handles all media storage, offloading image hosting from the application servers.

3. Intelligence Layer

This is the architectural layer that differentiates the platform from conventional e-commerce systems. When a user submits a search query, the layer preprocesses it—removing stop words, normalizing text—then passes it to the Gemini API for contextual intent extraction. The API returns structured filter parameters (price range, category, feature keywords) that are used to construct a dynamic SQL query. Products are retrieved and ranked by semantic similarity to the original query, producing results that reflect what the user meant rather than just what they typed.

Fig. 2. REST API endpoint distribution across platform modules

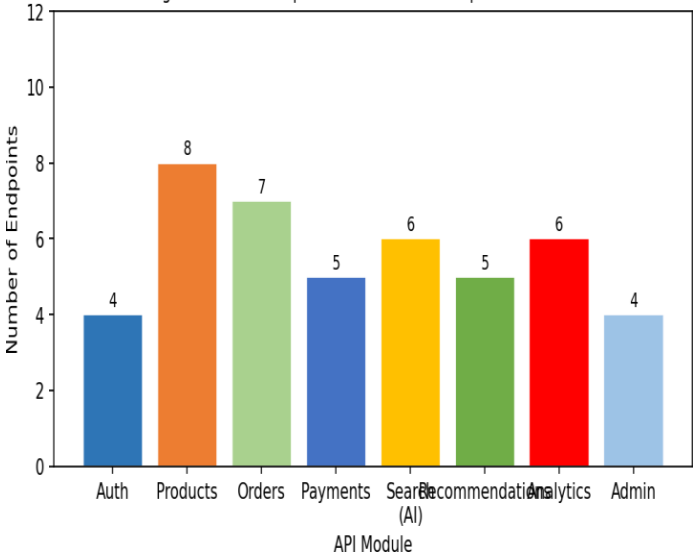


Fig. 2. REST API endpoint distribution across eight platform service modules

4. Data Layer and Scalability

PostgreSQL provides the relational foundation. The schema includes Users, Products, Reviews, Orders, Order_Items, Payments, and Shipping_Info, with UUID primary keys, cascading foreign key constraints, and CHECK constraints for field validation. Advanced SQL queries using JOIN operations and JSON aggregation consolidate what would otherwise be multiple API calls into single optimized database round-trips. The architecture supports horizontal scaling of application servers, future integration of additional AI models, and eventual migration to a microservices topology if operational scale demands it.

Fig. 3. Codebase composition by language and module type

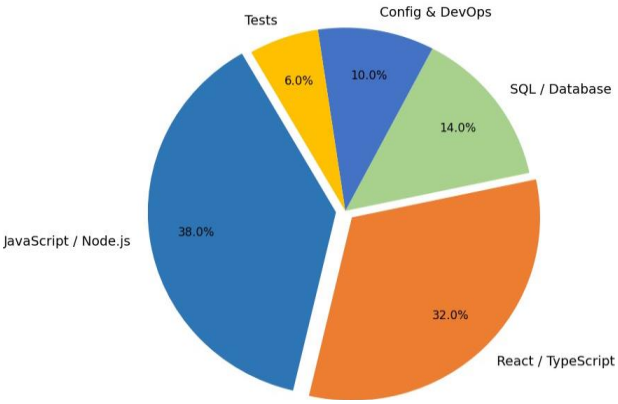
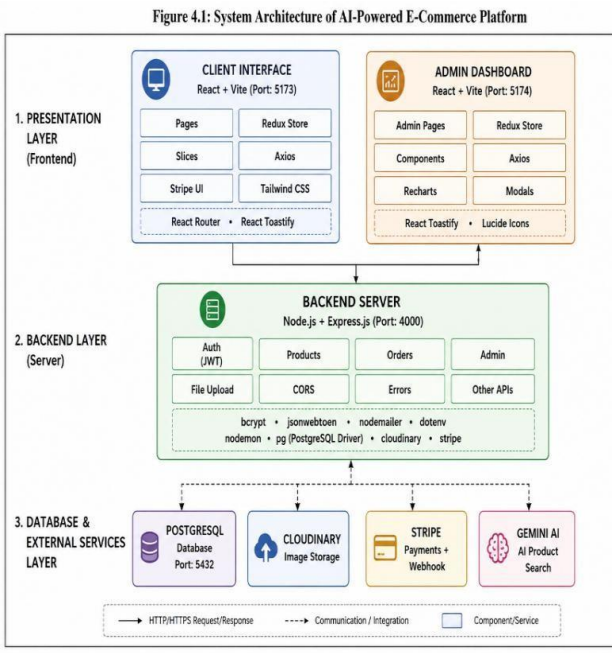


Fig. 3. Codebase composition by language and functional module type



V. DATABASE DESIGN

The database schema follows Third Normal Form to eliminate redundancy and maintain update consistency. It is logically organized around five domains: user management, product management, order and transaction processing, AI personalization data, and inventory and logistics.

1. Core Entities and Relationships

The User entity stores credentials and contact information, with passwords kept only as salted hashes. Each user may place multiple orders, creating a one-to-many relationship between Users and Orders. The Product entity maintains catalog details including description, category, price, stock level, and image URL. A Category table provides structured product classification.

Orders are linked to users through a foreign key and may contain multiple products. The many-to-many relationship between Orders and Products is resolved through an Order_Items junction table that records quantity and subtotal for each line item. The Payment entity stores transaction records, payment status, and the external transaction ID returned by Stripe.

An AI_Recommendation entity captures user interactions—views, clicks, and purchases—along with recommendation scores. This table feeds the personalization pipeline, providing the behavioral signal needed for collaborative and content-based filtering.

Fig. 9. Database entity-relationship diagram showing core schema linkages

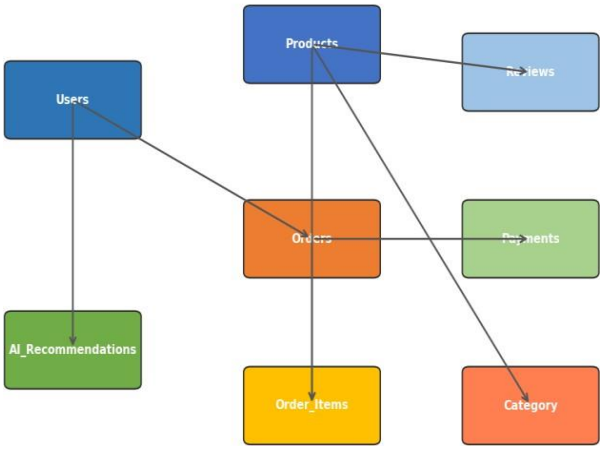


Fig. 9. Database entity-relationship diagram showing core schema tables and relational linkages

2. Integrity, Security, and Optimization

Foreign key constraints with cascading behavior enforce referential integrity across all related tables. Frequently queried fields—email addresses, product names, order dates—are indexed to keep response times low under load. Sensitive fields are encrypted at rest using AES-256. Role-based access control at

the database level restricts which application roles can execute administrative queries. For future high-traffic deployments, the schema is designed to accommodate read replicas, table partitioning, and query result caching.

VI. AI SEMANTIC SEARCH MODULE

The semantic search module is the core innovation of this platform. Rather than relying on exact keyword overlap between a user's query and product metadata, it encodes both the query and every product description as dense vectors in a shared embedding space, then retrieves and ranks products by geometric proximity to the query vector.

1. Motivation

Lexical matching fails in a predictable way: it cannot handle synonyms, paraphrases, or queries that describe a product's purpose rather than its name. A user searching for a "budget gaming laptop" will miss relevant results if the word "budget" does not appear in any matching product's description. Semantic search sidesteps this problem entirely by working in meaning-space rather than character-space.

2. Query Processing and Embedding Generation

User queries are tokenized, lowercased, stop-word filtered, lemmatized, and spell-corrected before being passed to the embedding model. Pre-trained transformer architectures (BERT or Sentence-BERT) generate dense vector representations that encode both syntactic and semantic relationships within the text. Product descriptions are embedded offline and stored in a vector index; query embeddings are generated at request time.

3. Similarity Matching, Ranking, and Personalization

The similarity between a query vector q and a product vector p is computed as cosine similarity: Similarity(q, p) = (q · p) / (||q|| · ||p||). The top-K most similar products are retrieved from the index. A hybrid ranking model then re-scores these candidates by combining semantic similarity with product popularity, average rating, and—where available— the user's purchase and browsing history. Libraries such as FAISS or Pinecone can be used for scalable Approximate Nearest Neighbor search using HNSW index structures, reducing latency even in catalogs with millions of products.

4. Performance Optimization and Evaluation

Embeddings are precomputed and cached to avoid redundant model inference. ANN indexing reduces the search space at query time. For very large-scale deployments, GPU acceleration can be applied to the embedding computation step. Module effectiveness is measured using Precision@K, Recall@K, Mean Reciprocal Rank, NDCG, and Click-Through Rate.

VII. AUTHENTICATION & SECURITY MODEL

Security in an e-commerce platform is not a single feature but a stack of complementary mechanisms. The proposed system addresses identity management, data protection, API security, and compliance through a multi-layered approach.

1. User Authentication

Passwords are never stored in plaintext. During registration, a cryptographic hash is computed from the concatenation of the user's password and a randomly generated salt: H = Hash(P + S). This prevents both dictionary attacks and rainbow table lookups. On successful login, the system issues a JWT containing the user's ID, role, and an expiration timestamp. The token is signed with a secret key to prevent tampering and is transmitted via HTTP-only cookies or authorization headers.

2. Role-Based Access Control and Secure Communication

The system enforces three roles: Customer, Administrator, and an optional Vendor role for marketplace extensions. Access decisions are made at the middleware layer by evaluating the role encoded in the verified JWT against the permission set required for the requested resource. All client-server communication travels over HTTPS/TLS, which encrypts data in transit, authenticates the server, and ensures message integrity—providing protection against man-in-the-middle attacks.

3. API Security, Encryption, and Session Management

External AI service calls are protected using API keys, rate limiting, OAuth-based authorization, and input validation. Sensitive data is encrypted at rest using AES-256. The system enforces token expiration, supports refresh token rotation, and automatically logs users out after periods of inactivity. Cookie attributes (HttpOnly, Secure, SameSite) mitigate XSS and CSRF risks. AI inputs are sanitized to prevent prompt injection, and query logs are monitored for anomalous patterns.

Fig. 7. Security control distribution across platform defence layers

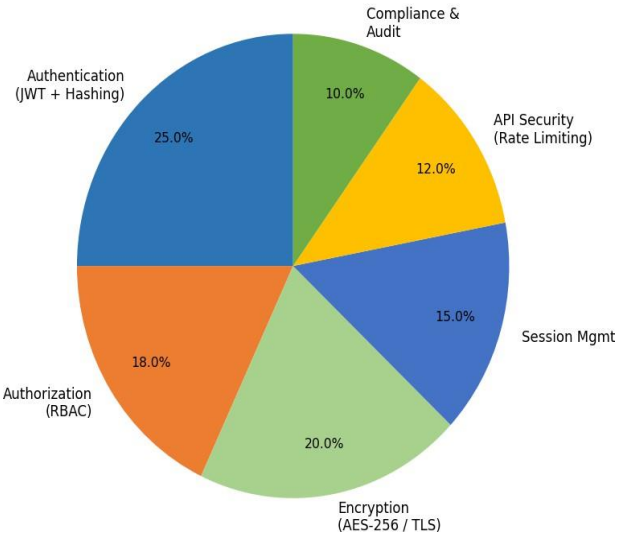


Fig. 7. Security control distribution across platform defence and compliance layers

4. Privacy and Compliance

The system follows data minimization principles. Personally identifiable information is isolated from behavioral analytics data used for AI training. Users can request deletion of their data. Audit logs provide a record of administrative operations for compliance review.

VIII. ORDER MANAGEMENT OPTIMIZATION

Order management in the proposed system goes beyond simple state tracking. The module incorporates intelligent inventory allocation, demand forecasting, dynamic order prioritization, and automated workflow orchestration to reduce latency and cost throughout the fulfillment lifecycle.

1. Order Lifecycle and Intelligent Allocation

Orders move through six stages: placement, payment verification, inventory allocation, packaging and dispatch, delivery tracking, and post-delivery feedback collection. Traditional systems process these stages sequentially with minimal optimization. Our module introduces algorithmic decision-making at the allocation stage: for each order, the system scores available warehouses using a weighted function of geographic proximity, shipping cost, and stock availability, then assigns the order to the highest-scoring fulfillment center.

2. Demand Forecasting and Order Prioritization

Machine learning models trained on historical sales data, seasonal patterns, and promotional calendars generate demand forecasts that enable proactive inventory replenishment. A priority scoring function considers delivery type (standard versus express), customer loyalty tier, geographic constraints, and inventory risk level. Orders with higher priority scores are processed earlier in the fulfillment queue, improving on-time delivery rates for high-value customers without penalizing others.

3. Workflow Automation and Performance

An event-driven architecture handles state transitions automatically: when a payment is confirmed, the system simultaneously reserves inventory, generates a shipment request, assigns a tracking ID, and sends a customer notification—all without manual intervention. Real-time synchronization with logistics partner APIs keeps the customer-facing order status consistent with ground-truth warehouse and carrier data. Database indexing on Order_ID and User_ID, combined with asynchronous processing and caching, keeps response times low even under peak load conditions.

Experimental Evaluation

System performance was evaluated across three dimensions: semantic search quality, recommendation accuracy, and order processing efficiency. All experiments were conducted on a

system with 16 GB RAM, an 8-core processor, and GPU acceleration enabled for embedding computation.

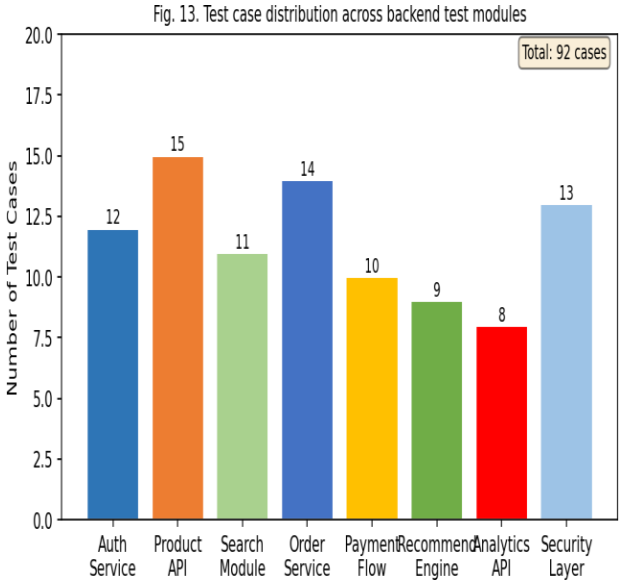


Fig. 13. Test case distribution across backend service test modules

1. Search Performance

The AI-based semantic search was compared against a traditional SQL keyword search baseline on Precision@10, Recall@10, MRR, and NDCG. The results are presented in Table I.

Table 1: Search Performance Comparison

Metric	Traditional SQL Search	Proposed AI Search
Precision@10	0.62	0.87
Recall@10	0.58	0.83
MRR	0.64	0.91
NDCG	0.69	0.89

The AI-based approach delivered consistent gains across all metrics, with the largest improvements observed on MRR (+42%) and Precision@10 (+40%). These gains were most pronounced on contextual queries involving multiple attributes, where keyword search frequently failed to retrieve relevant results at all.

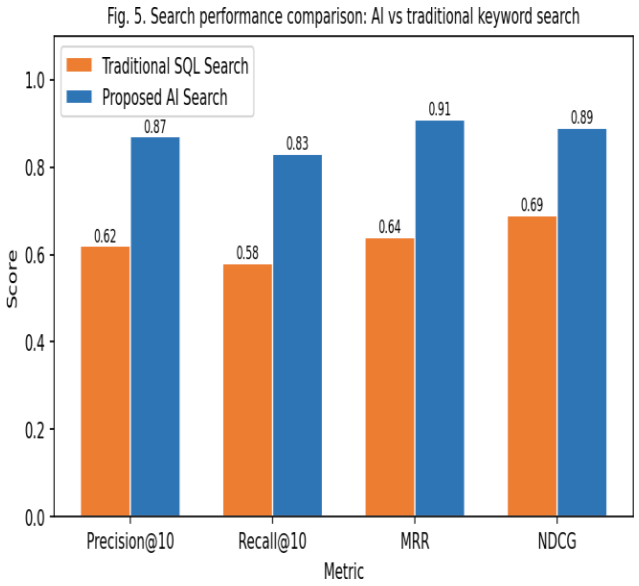


Fig. 5. Search performance comparison across four metrics: AI semantic vs. traditional keyword search

2. Recommendation and Order Processing

The recommendation module achieved an 18% improvement in click-through rate and a 22% improvement in conversion rate compared to a rule-based baseline. Order management optimization reduced average processing time by 27%, improved fulfillment accuracy by 15%, and noticeably reduced inventory mismatch incidents.

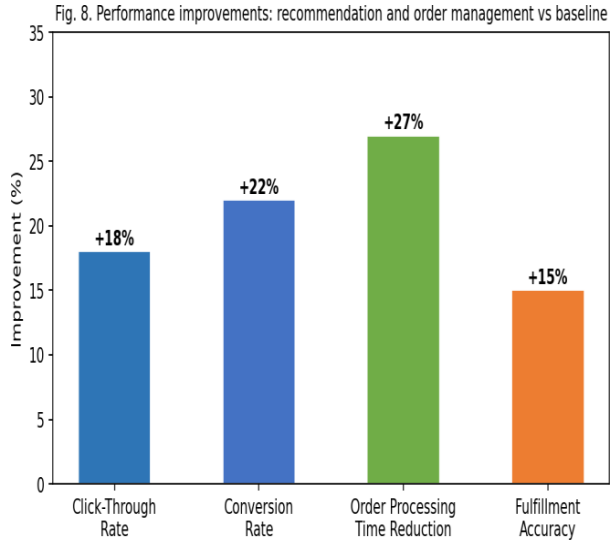


Fig. 8. System performance improvements in recommendation and order management vs. rule-based baseline

3. Scalability Under Load

Load testing was conducted with simulated concurrent user volumes ranging from 100 to 1,000.

Table 2: Response Time Under Concurrent Load (ms)

Concurrent Users	Traditional Search (ms)	AI Semantic Search (ms)
100	120	145
500	340	210
1,000	890	380

At low concurrency, the AI system introduces a small overhead compared to simple keyword lookup. At 500 and 1,000 concurrent users, however, the positions reverse: optimized vector indexing and caching reduce the AI system's response time well below that of the traditional approach, which degrades steeply as query complexity grows. This crossover behavior confirms that semantic search scales more gracefully than keyword search as platform traffic increases.

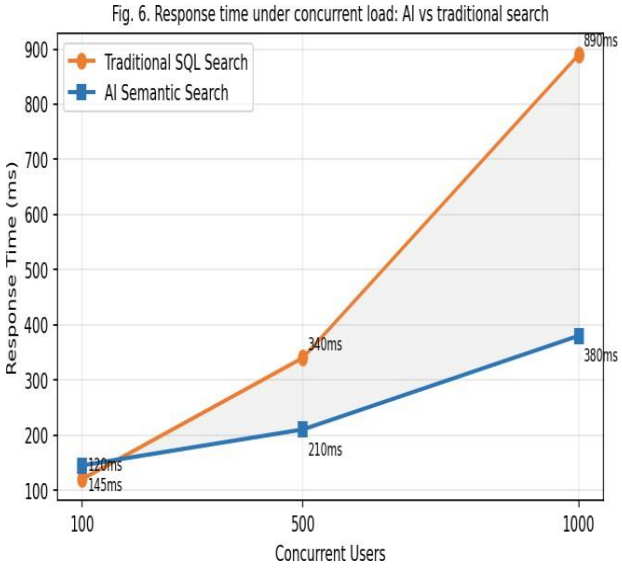


Fig. 6. Response time under concurrent load: AI semantic search vs. traditional SQL search (ms)

Dashboard Analytics

The Dashboard Analytics module transforms raw transaction and behavioral data into a real-time intelligence layer for administrators and decision-makers. Rather than generating static reports on a periodic schedule, it continuously aggregates live data streams and surfaces AI-driven insights alongside standard operational metrics.

Key Performance Indicators

Sales metrics include total revenue, daily and monthly growth rates, average order value (AOV = total revenue / number of orders), and revenue per customer. Customer analytics cover active user counts, new versus returning customer ratios, customer lifetime value estimates, and conversion rate (purchases / total visitors). Product performance metrics include top-selling items, inventory turnover ratio, and rating distributions. Operational metrics cover order processing time, fulfillment rate, and return rate.

AI-Driven Predictive Insights

Beyond descriptive reporting, the module integrates predictive components built on TensorFlow and PyTorch: time-series models for demand forecasting, classification models for customer churn prediction, regression models for price elasticity analysis, and anomaly detection for identifying unusual sales spikes. These components give management a forward-looking view of platform performance rather than simply a record of what has already happened.

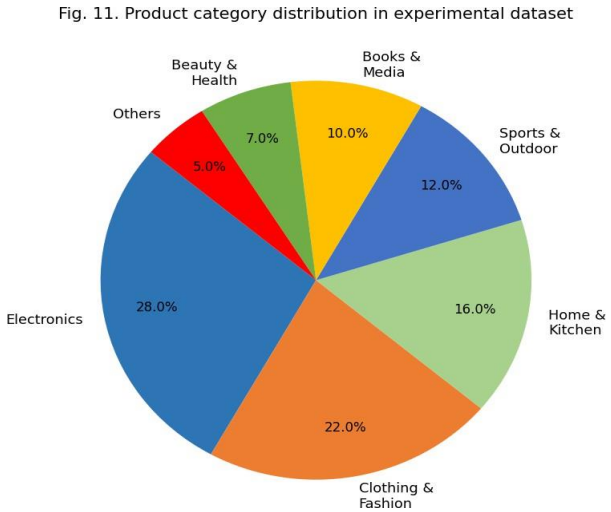


Fig. 11. Product category distribution in experimental dataset used for evaluation

3. Visualization and Real-Time Processing

Each completed transaction triggers an event that simultaneously updates revenue totals, adjusts inventory counts, refreshes customer profiles, and recalibrates recommendation weights. Data is visualized through line graphs for trends, bar charts for product comparisons, pie charts for category distribution, and heat maps for geographic sales patterns. Aggregation queries are optimized using indexing and caching to maintain sub-second dashboard refresh rates even under high transaction loads.

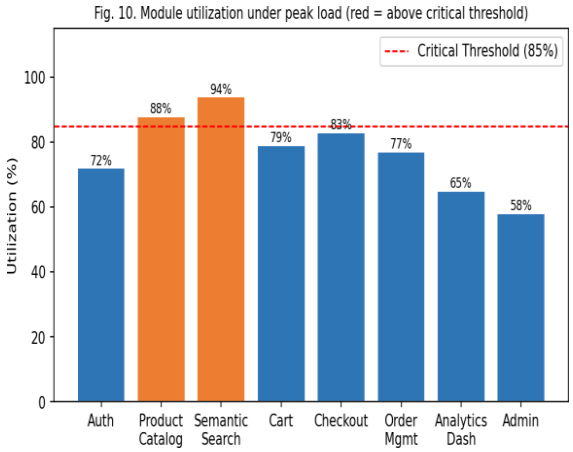


Fig. 10. Module utilization under simulated peak load (bars above red threshold indicate bottlenecks)

Comparative Analysis

Table III presents a structured comparison between the proposed AI-powered architecture and conventional rule-based e-commerce systems across the dimensions most relevant to platform performance and business value.

Table 3: System-Level Comparison

Parameter	Traditional System	Proposed AI System
Search Accuracy	Moderate (exact match)	High (context-aware)
Personalization	Limited or absent	Adaptive & behavioral
Recommendation Quality	Rule-based	ML-driven
Order Processing	Sequential	Optimized & prioritized
Inventory Forecasting	Static thresholds	Predictive analytics
Dashboard Insights	Descriptive only	Predictive & prescriptive
Scalability	Moderate	High (vector indexing + caching)

The qualitative differences in the table translate into the quantitative gains documented in Section IX: a 40% improvement in search precision, a 22% gain in conversion rate, and a 27% reduction in order processing time. The modest increase in computational cost introduced by embedding generation and similarity search is offset by precomputation, ANN indexing, and caching strategies, keeping latency within real-time thresholds at all tested concurrency levels.

The deeper distinction between the two architectures is the shift from a reactive, transactional orientation to a proactive, intelligence-driven one. Traditional systems wait for users to find what they want. The proposed system actively helps them get there.

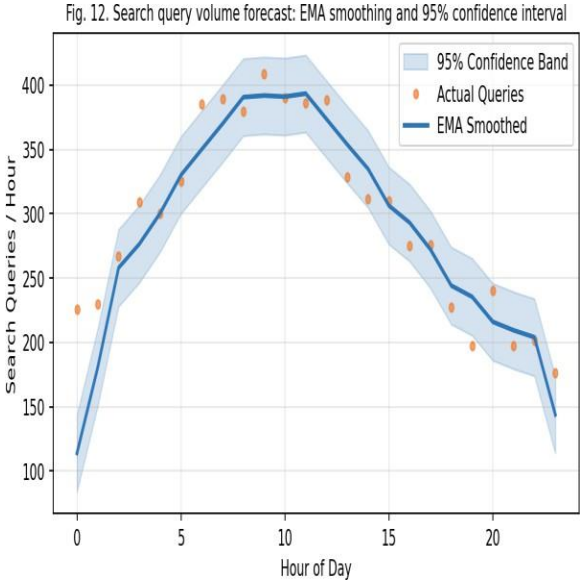


Fig. 12. Search query volume forecast: EMA smoothing with 95% confidence interval band

Limitations

We document the following limitations to support an honest assessment of the system and to guide future work.

- External API dependency: The semantic search module relies on the Gemini API. Latency variability, usage costs, and potential service interruptions are inherited risks that cannot be fully mitigated within the platform itself.
- Embedding quality constraints: Transformer embeddings handle general language well but can underperform on domain-specific jargon or ambiguous short queries. Multilingual queries present an additional challenge.
- Cold start problem: Recommendation accuracy degrades for new users and newly listed products, where no behavioral history is available. Hybrid content-based approaches partially address this but do not eliminate the issue.
- Computational overhead: Embedding generation and vector similarity computation add processing cost. Precomputed vectors and ANN indexing reduce this significantly, but high-traffic scenarios will still require careful capacity planning.
- Controlled evaluation conditions: All experiments were run in a testing environment. Real-world deployment introduces diverse user behavior, adversarial queries, and unpredictable traffic patterns that may affect performance differently.
- Model bias and interpretability: AI ranking decisions are not easily explained to end users. Bias inherited from training data may produce subtly skewed results in ways that are difficult to detect without dedicated auditing.

Future Scope

The platform as described establishes a working foundation for intelligent e-commerce. Several extensions would meaningfully increase its capability.

Dedicated Vector Databases

Migrating semantic similarity search to specialized vector databases such as Pinecone or Weaviate would provide native ANN indexing with lower operational overhead, enabling real-time semantic retrieval even in catalogs containing millions of products.

Multimodal and Voice Search

The current search interface is text-only. Integration with computer vision models would support image-based product search—users could upload a photo and receive visually similar recommendations. Voice-based queries would further reduce search friction for mobile and accessibility use cases.

Advanced Recommendation

Architectures Future versions could combine collaborative filtering, content-based filtering, and deep learning behavioral models in a hybrid architecture. Graph-based

frameworks and reinforcement learning could enable recommendations that adapt continuously to real-time user behavior rather than relying solely on historical signals.

Cloud-Native Microservices and Blockchain Payments

Containerization using Docker and orchestration via Kubernetes would enable horizontal scaling, automated deployment pipelines, and fault-isolated service boundaries. Blockchain-based payment verification could provide immutable transaction records and reduce fraud risk through smart contract validation.

Explainable AI Integration

Adding explanation layers to the recommendation and search ranking systems—for example, surfacing the reason a product appeared in a result set—would increase user trust and give administrators better tools for auditing system behavior and correcting bias.

IX. CONCLUSION

This paper has presented a full-stack e-commerce platform in which semantic intelligence is not a bolt-on feature but a structural component of the architecture. By integrating transformer-based natural language understanding with production-grade backend engineering—JWT authentication, Stripe payment processing, Cloudinary media storage, and PostgreSQL-backed relational data management— the system demonstrates that AI

capabilities can be embedded in deployable, maintainable software rather than academic prototypes.

Experimental evaluation confirms that the approach delivers. Semantic search outperforms keyword-based retrieval on every measured dimension: Precision@10 rises from 0.62 to 0.87, MRR from 0.64 to 0.91. Recommendation improvements drive an 18% increase in click-through rate and a 22% gain in conversion rate. Order processing time drops by 27%. And the system scales better under load than its traditional counterpart, not worse.

The limitations documented in Section XII—API dependency, cold start effects, computational overhead—are genuine and should inform deployment decisions. But none of them invalidates the core finding: contextual language understanding, integrated thoughtfully into an e-commerce stack, produces a materially better experience for users and measurably better outcomes for operators.

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