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Beyond the Black Box: A Semantic Explainable AI Framework for Transparent and Trustworthy E-Commerce Decisions

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Abstract: *Artificial intelligence has become an important part of modern e-commerce, supporting product recommendations, search ranking, customer-review analysis, and personalized shopping experiences. Despite these benefits, customers often receive recommendations without understanding the reasons behind them. This lack of transparency can make it difficult to distinguish a genuinely relevant suggestion from one influenced by popularity, incomplete information, or commercial priorities. Explainable Artificial Intelligence (XAI) offers a way to make these decisions more understandable. However, explanations are useful only when they communicate relevant evidence accurately rather than simply presenting convincing language. This paper examines the relationship between XAI, semantic analysis, and transparent decision-making in e-commerce, with particular attention to research trends during 2024, 2025, and 2026. It proposes a conceptual framework that connects customer preferences, product attributes, review sentiment, recommendation models, and evidence-based explanations. The framework is designed to explain why a product may be relevant, which features support the recommendation, and where conflicting information remains. The paper also discusses explanation faithfulness, customer privacy, review reliability, fairness, and the limitations of language-model-generated explanations. Its contribution is a practical design approach for connecting recommendation decisions with verifiable semantic evidence. Future implementation and user testing are required to determine whether this approach improves customer understanding and decision quality in real shopping environments*

Keywords: Explainable Artificial Intelligence, E-Commerce, Semantic Analysis, Explainable Recommender Systems, Natural Language Processing, Algorithmic Transparency, Customer Trust, Responsible AI.

I. INTRODUCTION

The growth of online shopping has changed how consumers discover, compare, and purchase products. An e-commerce platform may display thousands of products within a single category, making it difficult for customers to identify the most suitable option. Artificial intelligence helps address this problem by analyzing product characteristics, browsing patterns, purchase history, ratings, and customer feedback to generate personalized recommendations.

Although these systems can make product discovery more efficient, the reasons behind their decisions are not always visible. A customer might receive a recommendation for a smartphone without knowing whether the selection reflects camera quality, price, battery performance, previous browsing activity, or product popularity. When a system provides no meaningful explanation, customers must either accept the recommendation without understanding it or independently investigate the factors that may have influenced the result.

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Explainable Artificial Intelligence aims to reduce this information gap by making the behaviour and outputs of AI systems easier to understand. In e-commerce, explanations can help customers identify relevant product characteristics, understand trade-offs, and compare alternatives. They can also help developers investigate unexpected recommendations and examine whether a system relies on inappropriate or misleading signals.

Semantic analysis provides an additional opportunity to improve explanations. Customer reviews frequently contain detailed information that cannot be represented adequately by an overall rating. A review might praise a product's design while criticizing its durability. By identifying individual product aspects and the opinions associated with them, a semantic analysis system can represent these differences more clearly.

Research on aspect-based recommendation methods demonstrates the value of connecting detailed opinions with recommendation models [1]. Work on explainable recommendation systems and language-model-generated explanations also indicates that the communication of recommendation evidence is an important research direction [2], [3].

Nevertheless, generating an explanation is not the same as proving that a decision is correct. A fluent explanation may omit contradictory evidence or claim that a product matches a preference that the customer never expressed. Consequently, transparency must involve both understandable communication and verification of the evidence supporting the explanation.

This research proposes a conceptual framework that combines semantic analysis with explainable product recommendations. It focuses on three research questions:

How are recent developments in Explainable AI changing the transparency of e-commerce decisions?

How can semantic analysis convert customer preferences and product reviews into useful recommendation evidence?

What design and evaluation principles can make explanations understandable, reliable, and respectful of customer privacy?

The main contribution of this paper is a framework that treats explanation generation and explanation verification as connected stages of an e-commerce recommendation process.

II. RELATED WORK AND RESEARCH BACKGROUND

A. Artificial Intelligence in E-Commerce

AI-based recommendation systems help online retailers organize product information and identify items that may be relevant to individual customers. Content-based filtering compares product attributes with user preferences, while collaborative filtering uses patterns in user-item interactions. Hybrid systems combine these approaches to use multiple sources of information.

Valencia-Arias et al. examined research trends in AI-based e-commerce recommendation systems and identified areas such as sentiment analysis, data mining, and personalized recommendations as important directions for further investigation [4].

However, recommendation relevance and decision transparency are different objectives. A model may rank products effectively without providing a clear account of the evidence behind its ranking. The challenge is therefore to develop systems that consider both recommendation quality and the customer's ability to understand the result.

B. Explainable Artificial Intelligence

Explainable AI includes methods that provide information about a model's predictions, influential features, behaviour, or limitations. Some systems use inherently interpretable models, while others apply explanation techniques to more complex models after a prediction has been generated.

Ribeiro, Singh, and Guestrin introduced LIME, a method for explaining individual predictions through locally interpretable approximations [5]. Lundberg and Lee introduced SHAP, a unified framework for explaining model predictions using feature attribution values [6]. These methods provide useful foundations for understanding which inputs contribute to a prediction, although the interpretation depends on the method, model, and assumptions involved.

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For e-commerce, feature-level explanations can identify relevant product attributes or preference matches. However, a list of influential features may not be sufficient for every customer. A shopper may need a short explanation in everyday language rather than a technical description of model behaviour.

C. Semantic Analysis of Product Reviews

Semantic analysis examines the meaning and relationships expressed in text. In online shopping, it can help identify product features, customer opinions, comparisons, and contextual preferences.

Aspect-based sentiment analysis is particularly relevant because a single review can contain different opinions about different product characteristics. For example, a laptop review might praise the screen and keyboard while criticizing battery life. A system that identifies these aspects can provide more informative evidence than one that relies exclusively on an overall star rating.

Kim et al. presented AXCF, an aspect-based collaborative filtering approach that combines user-item relationships with sentiment information extracted from reviews [1]. Feng's 2025 study investigated e-commerce recommendations using web information extraction and sentiment analysis [7]. These studies illustrate how semantic information can contribute to more detailed product understanding.

However, reviews are not guaranteed to represent objective product performance. They may be outdated, subjective, contradictory, or manipulated. A responsible recommendation system should therefore identify the source of its evidence and communicate uncertainty where appropriate.

D. Explainable Recommendations and Natural-Language Generation

Traditional recommendation explanations may identify similar users, matching attributes, or historical interactions. Newer approaches also investigate the use of large language models to express recommendation evidence in natural language.

Said's review of large language models for recommendation explanations found that the directly relevant research identified in the review was still limited, highlighting the need for further development and evaluation [2]. Research on explainable e-commerce search has also examined how explanations can help users understand why particular search results are relevant [3].

Language models can make explanations more accessible, but their output must be checked against the underlying evidence. A recommendation system should not allow a language model to invent product specifications, fabricate review consensus, or attribute preferences to a customer without support.

E. Research Gap

The reviewed literature addresses several important areas, including recommendation accuracy, feature attribution, sentiment analysis, and explanation generation. However, these areas do not automatically form a single, verifiable process.

A remaining design challenge is to connect the recommendation model, semantic evidence, natural-language explanation, and validation mechanism so that each explanation can be traced to relevant information.

This paper addresses that design challenge through a conceptual framework. It does not claim that no previous system has combined these techniques; instead, it proposes a structured way to organize them around evidence-based transparency in e-commerce.

III. ANALYSIS OF RESEARCH TRENDS: 2024–2026

A. Research Developments in 2024

Research published in 2024 explored more detailed recommendation explanations and methods for integrating semantic information into recommendation models. Aspect-based collaborative filtering provided one example of how review opinions could be used to represent preferences at the product-feature level [1].

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Work on explainable deep recommendation networks also examined ways to provide global and individual explanations for complex recommendation models [8]. At the same time, the growing interest in large language models introduced new possibilities for communicating recommendations in ordinary language.

The important direction in 2024 was the movement from explaining recommendations only through general similarity toward explanations that could incorporate more specific features, opinions, and model evidence.

B. Research Developments in 2025

Research in 2025 continued to investigate the relationship between product information, sentiment analysis, recommendation quality, and transparency. Feng examined an e-commerce recommendation approach based on information extraction and sentiment analysis [7].

Tian et al. investigated explainable search results in e-commerce, focusing on helping users understand the relevance of search outcomes [3]. This is important because customers interact with both search-ranking systems and recommendation systems while shopping, and both can influence which products receive attention.

These developments suggest that transparency should not be limited to a product recommendation card. It can also be useful in search ranking, product comparison, and the interpretation of customer feedback.

However, the existence of these research directions does not demonstrate that every commercial platform has implemented them or that they always increase customer trust.

C. Research Developments in 2026

For 2026, the analysis should distinguish confirmed developments from broader research expectations. Current work can be examined in terms of personalized explanations, evidence verification, responsible AI deployment, and the need to evaluate explanations across different customer groups.

The European Union's AI Act includes transparency obligations for specified AI systems and AI-generated content. Its Article 50 provisions have an application date of 2 August 2026 for the relevant obligations, subject to their scope and exceptions [9]. These requirements should not be interpreted as a universal legal mandate for every e-commerce recommendation.

A central research question for this period is how to move from explanations that merely sound convincing to explanations that can be checked against the information and processes supporting the decision.

The following table summarizes the principal trends considered in this paper.

IV. EXISTING SYSTEM

A. Architecture of the Existing System

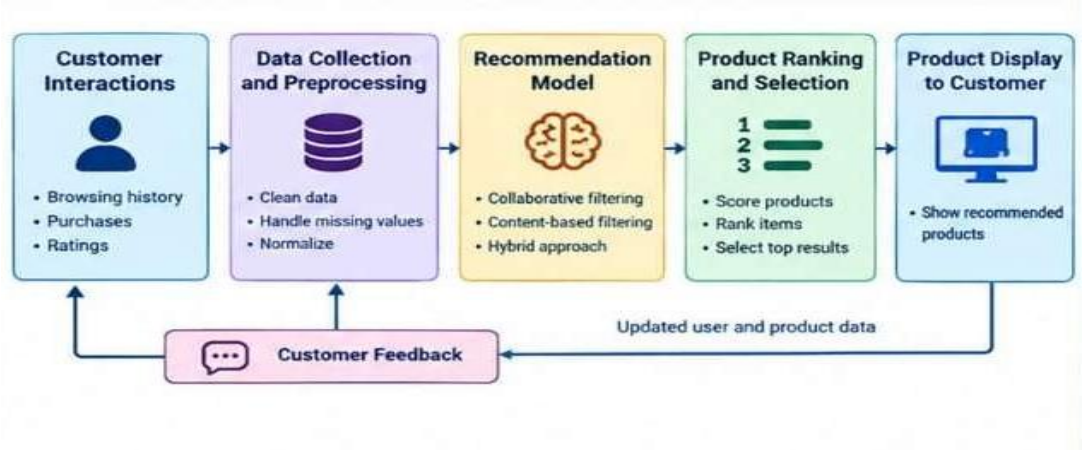


Figure 1. General Architecture of an AI-Based E-Commerce Recommendation System

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A conventional AI-driven e-commerce workflow receives product information and customer interactions, processes the available data, generates recommendations, and displays ranked products. The exact implementation varies across platforms.

B. Limitations of Existing Approaches

Limited explanation of ranking: Customers may see a product at the top of a page without knowing which factors influenced its position.

Loss of review detail: Aggregate ratings can conceal different opinions about individual product features.

Potential bias in available data: Historical interactions may favour already popular products and limit the visibility of less frequently selected alternatives.

Insufficient communication of uncertainty: A recommendation can appear definitive even when the product information is incomplete or customer reviews conflict.

Difficulty verifying generated explanations: A natural-language explanation may contain statements that cannot be traced to the actual recommendation evidence.

Privacy concerns: Personalizing explanations may require customer data that should be minimized and protected.

These limitations motivate the proposed framework. They are possible weaknesses of existing approaches, not claims that every current e-commerce system suffers from all of them.

V. PROPOSED SEMANTIC EXPLAINABLE AI FRAMEWORK

A. Framework Overview

The proposed framework combines recommendation generation, semantic interpretation, evidence selection, naturallanguage explanation, and validation. Its purpose is to make product recommendations more understandable while maintaining a clear connection between the recommendation and the information used to justify it.

The framework consists of six modules:

- Data preparation and privacy protection.
- Semantic analysis of product information and customer reviews.
- Recommendation generation and ranking.
- Evidence selection.
- Natural-language explanation generation.
- Explanation validation and monitoring.

B. Proposed System Architecture

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Figure 2. Proposed Semantic Explainable AI Framework for E-Commerce

The main distinction from the generalized existing workflow is the explicit connection between evidence selection, explanation generation, and validation. The framework is a proposed design, not an implemented system with demonstrated performance.

C. Data Preparation and Privacy Protection

The first module prepares the information needed for recommendation and explanation. Depending on the platform and applicable permissions, the inputs may include product attributes, customer preferences, review text, and product ratings.

Preprocessing can include removing duplicate records, handling missing values, normalizing text, and identifying relevant product attributes. Privacy controls should limit data collection to what is necessary for the task and protect personal information throughout processing.

D. Semantic Analysis Module

The semantic analysis module identifies meaningful relationships in customer queries, product descriptions, and reviews. It may use natural language processing, sentence embeddings, aspect-based sentiment analysis, or other suitable textanalysis techniques.

For example, consider these statements:

"The headphones are comfortable."

"The battery lasts longer than expected." □ "The sound quality is disappointing."

The module can associate the opinions with the aspects *comfort*, *battery life*, and *sound quality*. This structured information helps the recommendation system identify both strengths and weaknesses relevant to a customer's preferences.

E. Recommendation and Evidence Selection

The recommendation engine ranks candidate products using an appropriate method, such as content-based filtering, collaborative filtering, or a hybrid approach.

The evidence selection module then identifies which available facts can support an explanation. These might include a product's listed price, a stated technical specification, or relevant review comments.

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Importantly, the explanation must not confuse correlation with causation. If a product was frequently purchased by customers with similar browsing patterns, that does not prove that the product is objectively better or that a particular feature caused the recommendation.

F. Natural-Language Explanation Generation

The explanation module converts verified evidence into clear language that an ordinary shopper can understand. It should preserve the meaning of the evidence and avoid unsupported claims.

For example:

"This product is within your selected budget and its listed specifications match your preference for wireless connectivity. Reviews are positive about comfort, although feedback about battery life is mixed."

This is an illustrative example. A real system should display such an explanation only if its product information and review evidence support each statement.

The explanation should also distinguish explicit preferences from inferred interests. If a customer has not stated a preference for a particular brand, the system should not present that preference as a known fact.

G. Explanation Validation

Before presenting the explanation, the system should verify that each factual statement is supported by an identifiable source.

The validation module should check:

Whether product specifications match the catalogue.

Whether review summaries accurately represent the available reviews.

Whether the explanation is consistent with the recommendation evidence.

Whether uncertainty or conflicting opinions are communicated appropriately.

Whether unnecessary personal information is revealed.

If the evidence is insufficient, the system should produce a more limited explanation or withhold the unsupported claim.

H. Semantic Explanation Workflow

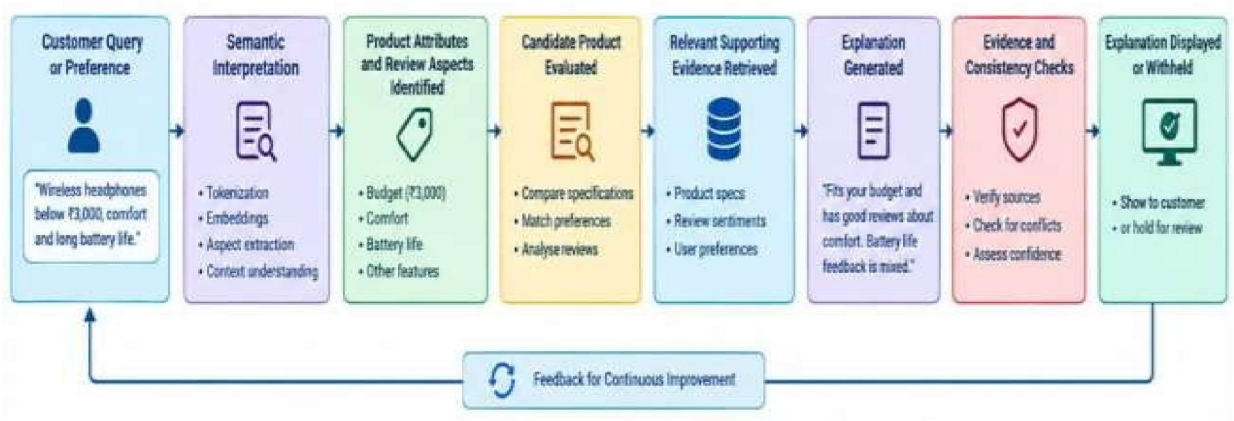


Figure 3. Workflow for Generating Evidence-Based Explanations

This workflow separates prediction from explanation. The recommendation model selects a candidate product, while the subsequent stages identify and communicate the evidence that supports the recommendation.

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VI. ILLUSTRATIVE APPLICATION AND EVALUATION METHODOLOGY

A. Illustrative Shopping Scenario

Consider a customer searching for wireless headphones within a budget of ₹3,000. The customer prefers comfortable ear cushions and long battery life.

A conventional recommendation system might rank products based on historical interactions, product characteristics, or popularity. However, a ranking alone does not explain whether the recommended headphones satisfy the customer's most important requirements.

Under the proposed framework, the system identifies the customer's budget and preferences, examines available product specifications, and analyzes relevant review aspects. It then selects a product and prepares an explanation based on the evidence available.

An appropriate explanation might be:

"This model fits your selected budget and has favourable customer feedback about comfort. Reviews contain mixed opinions about battery life, so comparing this feature with other models may help you make a better-informed choice."

This example illustrates the intended behaviour of the framework. It is not the output of a real experiment, and it does not establish that customers will necessarily trust or prefer the explanation.

B. Research Methodology

This paper uses a conceptual research approach supported by selected literature on explainable AI, recommendation systems, semantic analysis, and AI transparency. The selected works provide technical background for the proposed framework and help identify design challenges.

The paper does not claim to be an exhaustive systematic literature review. It also does not report a newly trained model, a completed customer survey, or experimentally measured performance.

C. Proposed Experimental Evaluation

A future implementation could compare two systems:

Baseline: A recommendation model that ranks products without the proposed evidence-based explanation pipeline.

Proposed system: The same or a comparable recommendation model combined with semantic evidence selection, explanation generation, and validation.

To make the comparison meaningful, both systems should be evaluated under equivalent data conditions.

Potential evaluation metrics include:

Recommendation quality: Precision@K, Recall@K, and Normalized Discounted Cumulative Gain (NDCG@K), where suitable ground-truth relevance data are available.

Evidence accuracy: The proportion of explanation claims supported by product records or relevant review evidence.

Explanation faithfulness: The degree to which the explanation reflects the actual recommendation process rather than an unrelated or post-hoc justification.

Comprehensibility: Whether customers understand the explanation and can identify the reasons supporting the recommendation.

Perceived fairness and trust: Evaluated through a properly designed user study with appropriate consent and clearly defined survey measures.

Privacy and robustness: Evaluated through data-minimization checks, access controls, and tests involving incomplete, contradictory, or manipulated inputs.

The evaluation should consider both recommendation performance and explanation quality. A system should not be considered successful merely because its explanations sound convincing.

VII. DISCUSSION

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The proposed framework highlights the importance of connecting recommendation decisions with meaningful evidence. Semantic analysis can help convert unstructured reviews and customer queries into structured information about product characteristics and user preferences. Explainability methods can then communicate the relevant information in a form that supports human understanding.

However, the relationship between explanation and trust is not automatic. A longer explanation may be more detailed but harder to understand. A shorter explanation may be easy to read but omit an important limitation. An explanation that emphasizes positive reviews while ignoring contradictory opinions may mislead customers even if the individual positive statements are factually correct.

Another concern is the difference between model interpretation and natural-language explanation. Feature-attribution techniques such as LIME and SHAP provide information about model behaviour under their respective assumptions [5], [6]. A language model can help express information in accessible terms, but fluent wording does not establish faithfulness. The explanation must remain connected to the evidence and the actual recommendation process.

The framework also raises practical questions about privacy. Customer browsing patterns and purchase histories may improve personalization, but collecting or revealing unnecessary personal information can reduce confidence in the system. A responsible design should provide useful explanations while limiting personal-data exposure.

Finally, the proposed approach may not be equally suitable for every product category. A simple recommendation based on a clearly stated price preference may require only a short explanation, whereas a high-value electronic product may benefit from a comparison of multiple specifications and conflicting reviews. Explanation depth should therefore reflect the decision context and the needs of the user.

VIII. CONCLUSION AND FUTURE SCOPE

Explainable AI and semantic analysis offer a promising direction for making e-commerce decisions more understandable. By connecting customer preferences, product attributes, review opinions, and recommendation evidence, the proposed framework provides a structured approach to generating explanations that are both accessible and verifiable. Its main emphasis is that transparency should involve more than presenting a convincing sentence: the explanation should accurately communicate supporting evidence, acknowledge uncertainty, and avoid exposing unnecessary personal information. Because this study proposes a conceptual framework rather than reporting a completed implementation, its practical benefits remain to be tested. Future work should implement the architecture, evaluate it using a suitable ecommerce dataset, and conduct user studies to examine explanation quality, customer comprehension, fairness, and trust. Additional research could explore multilingual semantic analysis, resistance to manipulated reviews, and privacypreserving personalization. These developments may help online shopping platforms provide recommendations that are not only relevant but also easier for customers to understand and evaluate.

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