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Best Buy: An AI–Based Multi–Platform Price and Sentiment Analysis Assistant

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Abstract: *The growth of e–commerce has made the same product available on multiple platforms that differ in price, delivery time and seller reliability [1]. Manually comparing prices, reading large volumes of reviews and checking seller trustworthiness is time-consuming. This paper presents Best Buy, an AI-driven web application that aggregates a product's information from several marketplaces, performs sentiment analysis on customer reviews and computes a composite trust score that jointly considers quality, ratings, sentiment, price competitiveness, shipping speed and seller reliability [3, 4]. The system outputs an explanation-driven dashboard that highlights the best overall deal instead of only the cheapest option, along with alternative offers and detailed price and trust comparisons. Experiments on real-world product data show that the proposed approach can effectively summarize multi-platform information and assist users in making safer and more informed purchasing decisions [5, 6]..*

Keywords: Sentiment Analysis, Price Comparison, Trust Score, E-commerce, Recommendation System

I. INTRODUCTION

The rapid expansion of e-commerce platforms such as Amazon, Flipkart, Croma and Ajio has reshaped the way consumers discover and purchase products online [1, 2]. For many popular items, identical or near-identical products are simultaneously listed on multiple platforms with different prices, discount structures, delivery times and seller reputations. Traditional price comparison tools help users identify the lowest price, but they typically neglect qualitative aspects such as customer sentiment, rating distributions and seller reliability, which are critical in avoiding fraudulent sellers, counterfeit items and poor post-purchase experiences [3, 4]. As a result, users are often forced either to rely solely on price or to manually browse reviews and ratings across several platforms before committing to a purchase.

Recent advances in sentiment analysis and opinion mining have shown that opinions automatically extracted from user reviews can serve as reliable indicators of product quality and seller behaviour [6, 7]. At the same time, trust-aware recommendation models emphasize that notions of trust and reliability should complement numerical ratings and prices when supporting decision making [8]. However, there is limited work that integrates multi-platform price analytics with review-level sentiment and trust modelling in a single, user-friendly application targeted at end consumers.

This paper proposes *Best Buy*, an AI-based assistant that addresses this gap by combining multi-site data aggregation, sentiment analysis and trust-score computation within a unified web platform. For a given product, the system automatically collects prices, ratings, textual reviews and seller details from several e-commerce sites, applies natural language processing (NLP) techniques to infer sentiment from the reviews and computes a composite trust score that

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jointly reflects quantitative and qualitative signals. The resulting information is presented through an interactive interface that highlights the most trustworthy offer, explains the factors influencing the trust score and provides personalized dashboard analytics such as price-drop alerts and high-trust categories. Through this integration of price comparison, sentiment analysis and trust modelling, the proposed system aims to support online shoppers in making decisions that balance cost with reliability and overall value.

II. PROPOSED SYSTEM

The *Best Buy* application offers a unified interface for intelligent online shopping support. Fig. 1 shows the landing page, which highlights key features such as verified sellers, best price guarantee and fast shipping and invites users to log in to start analysis. After authentication, users are taken to the search interface, where products can be queried and selected for further analysis.

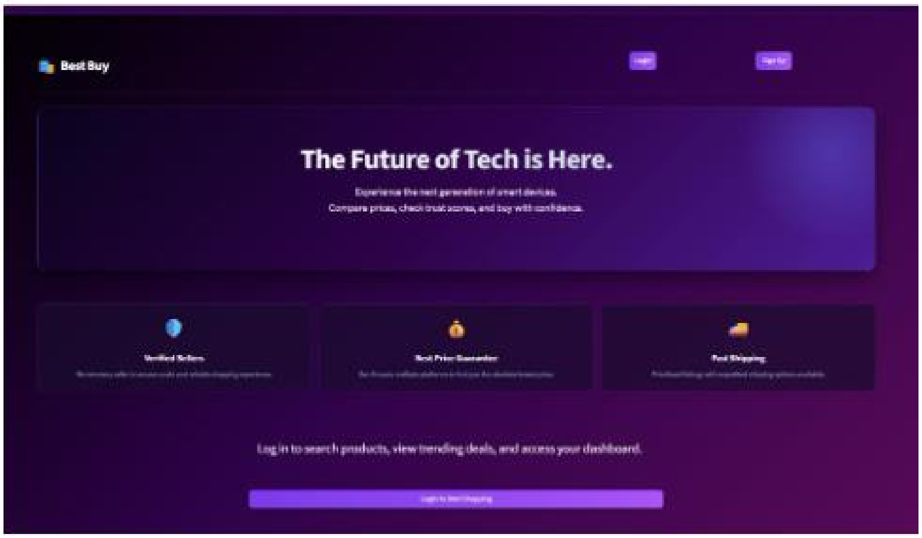

Figure 1: Landing page of the Best Buy application showing key features such as verified sellers, best price guarantee and fast shipping widgets.

Internally, the operation of *Best Buy* follows a layered architecture connecting the front-end, data aggregation services, sentiment analysis engine, trust-score computation and dashboard services. Fig. 2 illustrates the overall workflow: a user search triggers product matching across platforms, data retrieval, sentiment analysis, trust-score computation and finally visualization of recommendations and dashboard insights. This modular design allows each component to be updated or scaled independently while preserving a clear separation between presentation, analytics and storage layers.

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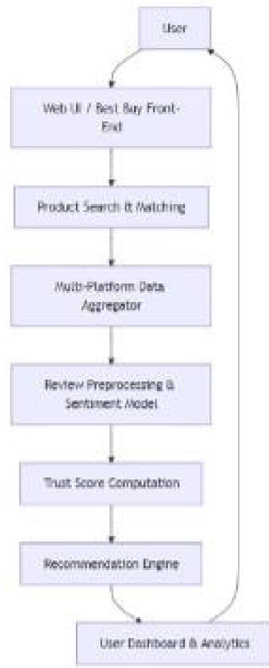

Figure 2: Overall system architecture and workflow of the Best Buy application.

III. SYSTEM OPERATION

When a logged-in user begins typing a product name, the system queries its index and returns matching products as suggestions, as shown in Fig. 3. This interaction improves usability and ensures that the selected product can be accurately mapped across multiple e-commerce platforms. Once the user confirms a product, the application triggers the data aggregation pipeline. Each supported platform is queried using either official APIs or controlled scraping of the public product page (subject to terms of use) [9], and the system extracts the effective price, discount, average rating, number of ratings, textual reviews and seller details.

The collected reviews are pre-processed and passed to the sentiment analysis module, where a transformer-based model classifies them as positive, negative or neutral [10, 6]. Price and rating information is normalized to a common scale, and the trust model described in Section 4 is applied to compute a trust score for each platform. Fig. 4 shows the analysis page for a

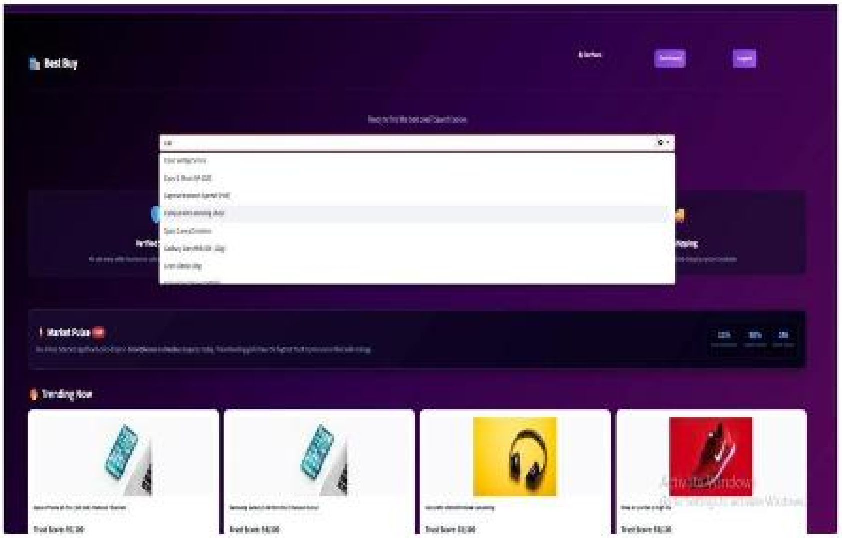

Figure 3: Product search page with auto-complete suggestions and trending products.

sample product: the system highlights the top recommendation along with a visual trust bar and presents a comparison table summarizing prices and trust scores of alternative platforms, enabling the user to understand the trade-offs between cost and reliability.

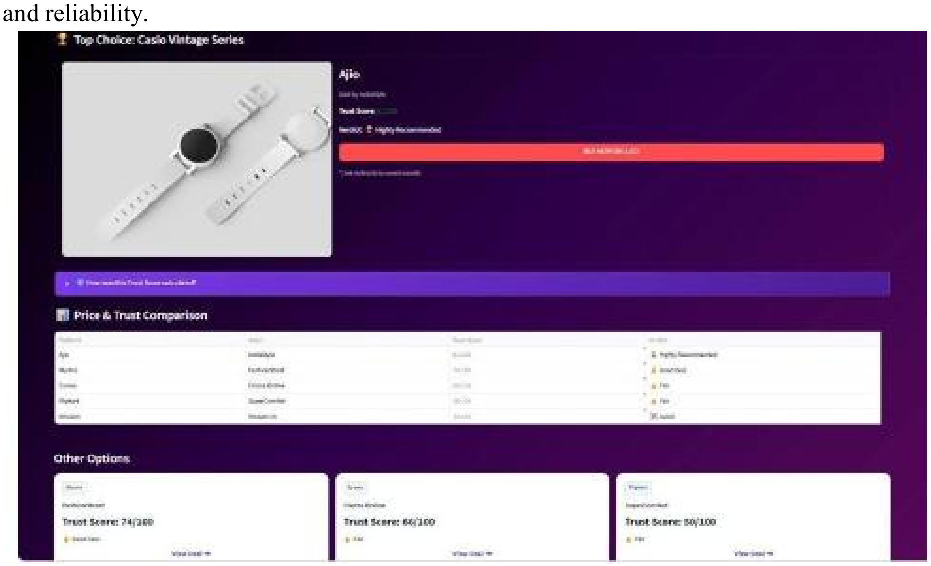

Figure 4: Product analysis page with top recommendation, trust bar and price & trust comparison table.

To obtain real-world data, *Best Buy* integrates with popular e-commerce platforms. Fig. 5 illustrates an example Ajio page for the Casio Vintage Series watch, from which product metadata, prices, ratings and reviews are collected and normalized inside the system. This cross-platform perspective allows the application to present a holistic view of the market for a particular product rather than focusing on a single retailer.

The dashboard summarises each user's activity and market-level analytics. It displays the number of categories and products tracked, the average market trust and AI-generated sugges-

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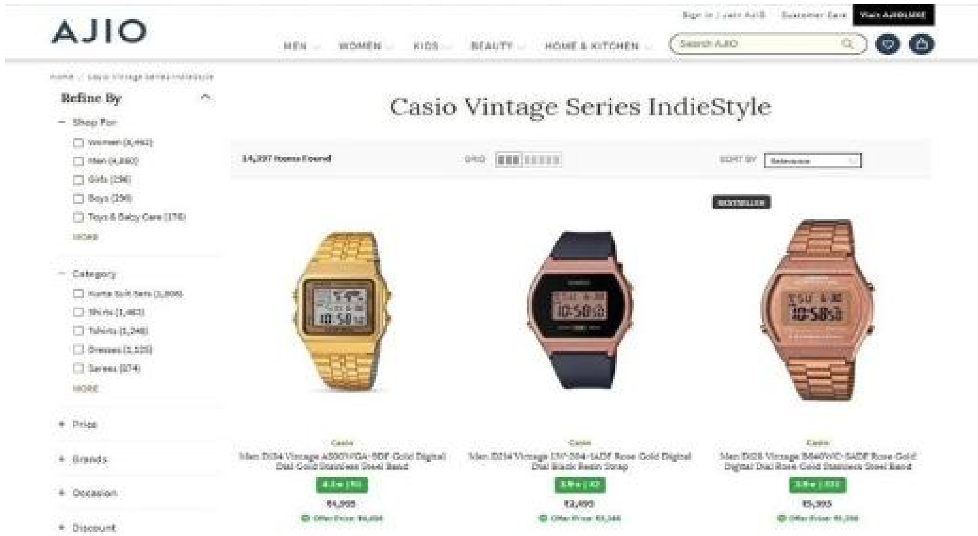

Figure 5: Example external Ajio product page used as a data source for prices, ratings and reviews.

tions such as price-drop alerts, high-trust categories, trending switches and newly added verified sellers. An example dashboard view is shown in Fig. 6, which demonstrates how aggregated trust information can be presented in a concise and actionable form.

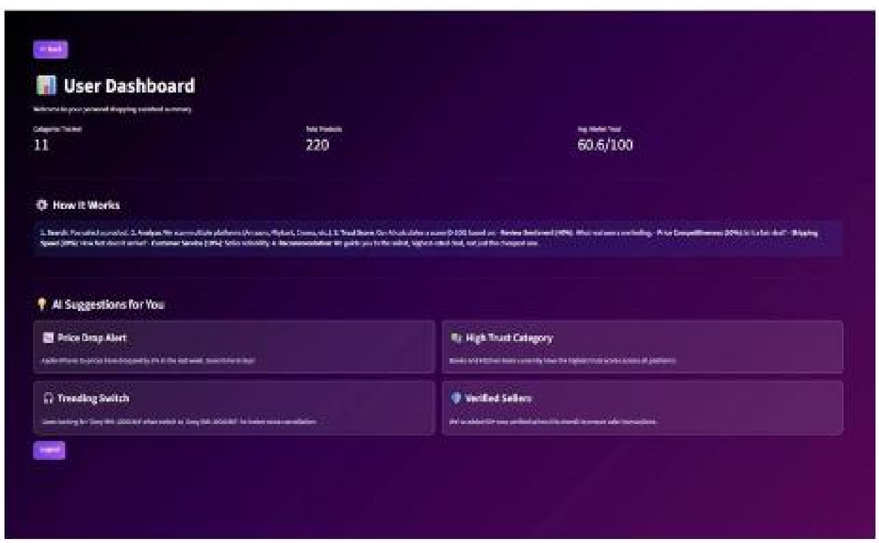

Figure 6: User dashboard showing tracked categories, products, average market trust and AI suggestions.

IV. MATHEMATICAL MODEL

Let P be a product selected by the user and let $\{S_1,S_2,\ldots,S_n\}$ denote the set of platforms where P is available. For each platform S_i, the objective is to compute a trust score T_i in the range $[0,100]$ that captures both quantitative and qualitative aspects of the offer [8]. The model is based on a set of normalized features.

For each platform S_i, the average product rating $r_i$is obtained from the corresponding star rating and scaled to $[0,1]$. Sentiment polarity $s_i$is defined as the fraction of positive reviews, where each review label is determined by the

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sentiment classifier [6]. Price competitiveness c_i reflects how close the observed price p_i is to the best available price and is computed as

$$c_i = 1 - \frac{p_i - p_{\min}}{p_{\max} - p_{\min} + \epsilon},$$

where $p_{\min}$ and $p_{\max}$ are the minimum and maximum prices across all platforms and ϵ is a small constant to avoid division by zero. Shipping speed d_i is derived from the expected delivery time and normalized so that faster delivery corresponds to higher values, while seller reliability q_i is obtained from the seller's rating and verified-seller status [4].
The composite trust score is modelled as a weighted linear combination of these features:

$$T_i = 100 \times (w_r r_i + w_s s_i + w_c c_i + w_d d_i + w_q q_i),$$

where $w_r + w_s + w_c + w_d + w_q = 1$ and all weights are non-negative. In the current implementation the weights are empirically set to

$$w_r = 0.25,\ w_s = 0.25,\ w_c = 0.20,\ w_d = 0.15,\ w_q = 0.15,$$

so that user experience and sentiment contribute half of the total score while price, shipping and seller reliability account for the remainder. The recommended platform S^* is then

$$S^* = \arg\max_{S_i} T_i.$$

To provide an interpretable output, the trust score is mapped to qualitative verdicts using thresholds $0 \le \tau_1 < \tau_2 < \tau_3 < \tau_4 \le 100$. Scores above τ_4 are labelled as "Highly Recommended", scores between τ_3 and τ_4 as "Good Deal", scores between τ_2 and τ_3 as "Fair", and scores below τ_2 as "Avoid". These thresholds can be tuned based on user feedback or validation experiments in future work.

V. IMPLEMENTATION AND RESULTS

The front-end of the system is implemented using a modern JavaScript framework with reusable components for the landing page, search interface, analysis view and dashboard. The back-end uses Python with a RESTful API that orchestrates product matching, data aggregation, sentiment analysis and trust-score computation [7]. A relational database stores normalized product information, reviews and user profiles. The sentiment module is based on a fine-tuned transformer model which performs multi-class classification of reviews into positive, neutral and negative categories [10].

The system was evaluated on popular products for which listings exist on at least three major platforms. For each product the platform selected by the proposed trust score was compared with a baseline that simply chooses the lowest price. In many cases the baseline selected a low-rated or poorly reviewed seller, whereas the proposed approach recommended a slightly higher priced but markedly more trustworthy option, demonstrating the benefit of combining price with sentiment and trust indicators [1, 3]. Informal user feedback further suggested that the unified dashboard and explicit explanation of the trust score made it easier for users to understand why a particular platform was suggested and increased their confidence in the final purchase decision.

VI. CONCLUSION

This paper presented *Best Buy*, an AI-based multi-platform assistant that unifies price comparison, sentiment analysis and trust modelling for online shopping. By aggregating information from several e-commerce sites and computing an interpretable trust score, the system helps users identify offers that optimize both cost and reliability. The architecture is modular, the mathematical model is transparent and the interface is designed to be accessible to everyday users.

Future work includes learning the trust-score weights automatically from user feedback, extending coverage to more platforms and product categories, and incorporating richer explanation mechanisms, such as aspect-level summaries of review sentiment or counterfactual recommendations. In the longer term, the framework could be integrated with personal financial assistants or browser extensions to provide real-time decision support at the point of purchase.

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