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Comparative Study on Smart Buy

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Abstract:
The rapid growth of e-commerce has provided consumers with a wide range of products and purchasing options, but comparing prices, discounts, product quality, reviews, and availability across multiple platforms remains time – consuming and difficult. This study presents an AI-powered real-time price comparison system designed to provide users with accurate, personalized, and data-driven purchasing assistance. The proposed system integrates real-time web scraping and intelligent product matching to collect and align product information from multiple e-commerce platforms, addressing differences in product names, formats, and website structures. Machine learning techniques are incorporated for price prediction and purchase-timing analysis, enabling users to understand price trends, review and sentiment analysis, product ratings, discounts, availability, and brand-related factors to provide comprehensive product evaluation. Image-based product identification can also support faster product discovery, while automated price-drop alerts help users monitor desired products. In addition, adaptive scraping and analytical dashboards can improve the reliability, visualization, and interpretation of continuously changing e-commerce data. Privacy-preserving approaches such as federated learning provide potential support for collaborative pricing intelligence without directly sharing sensitive data. By integrating these capabilities into a unified and user-friendly platform, the proposed system aims to reduce manual comparison, improve purchasing decisions, identify genuine value beyond price alone, and provide timely and personalized insights for online shoppers.

Keywords — **Artificial Intelligence, Machine Learning, Real-Time Price Comparison, Web Scraping, Product Matching, Price Prediction, Recommendation System, Sentiment Analysis, Price Alerts, E-Commerce Analytics, Personalized Shopping**

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I. INTRODUCTION

The rapid growth of e-commerce has changed the way consumers search for and purchase products. The availability of Similar products across multiple online platforms provides consumers with more choices, but it also makes the process of finding the best deal increasingly difficult. Users often need to visit different websites, search for the same product repeatedly, and, manually compare prices, discounts, ratings, reviews, and vailability. This process in time-consuming and may lead to decision fatigue [1], [2]. Existing research has explored web scraping techniques for colleting product information from multiple e-commerce platforms [3], [4]. However, differences in website structures, dynamic content, and inconsistent product names make reliable cross-platform product comparison challenging [5], [6]. Several studies have introduced intelligent product matching and recommendation techniques to improve online shopping. Fuzzy matching approaches can identify similar products despite differences in product names and product descriptions [6], [7]. Personalized recommendation

systems can consider user preferences, product characteristics, and previous interactions to provide more relevant results [8], [9]. Other studies have incorporated price prediction using machine learning algorithms such as Random Forest and XGBoost, using historical prices, product categories, brands, rating, reviews, competitor prices, and seasonal trends to predict future price behaviors [10], [11]. Natural Language Processing techniques have also been applied to analyses customer reviews and product descriptions. Sentiment analysis can identify consumer opinions and provide additional information about product quality beyond numerical ratings [12], [13]. Advanced language models have further improved contextual understanding of customer reviews and product-related information [14]. In addition, automated monitoring systems have introduced price-drop alerts, availability notifications, discount tracking, and interactive dashboards to reduce the need for continuous manual monitoring. Although these studies demonstrate significant progress, many existing systems concentrate on individual functions such as web scraping, price comparison, product recommendation, sentiment analysis, or price prediction [3], [10], [12]. Some systems depend on static datasets, while others have limited platform coverage, product matching capabilities, personalization, or real-time adaptation [5], [6]. Existing research also identifies scalability and real-time product alignment as important challenges in e-commerce comparison systems. Therefore, there is a need for an integrated system that combines real-time product data collection, intelligent product matching, price comparison, price prediction, sentiment analysis, personalized recommendations, and automated price alerts within a unified platform. The proposed system aims to develop n AI-powered real-time price comparison platform that collects product information from multiple e-commerce sources and provides users with comprehensive purchasing assistance. The system compares product prices and offers, identifies equivalent products across platforms,
analyses customer reviews and sentiment, predicts future price trends, provides personalized recommendations, and generates price alerts. By integrating these capabilities, the proposed system aims to reduce manual comparison, save users time, and support reliable and cost-effective purchasing decisions.

A. Problem Statement

Consumers currently face difficulty in identifying the best product and most suitable price across multiple e-commerce platforms because product price, discounts, availability, specifications, ratings, and reviews vary continuously between websites. Existing price comparison systems may provide real-time price information, but many lack accurate cross-platform product matching, dynamic-content handling, advanced analytics, personalization, or future price prediction. Furthermore, selecting a product based only on its lowest price does not necessarily represent the best purchasing decision because customer sentiment, product quality, brand, rating, offers, availability, and historical price trends can also influence product value. Although previous studies have separately addressed web scraping, product matching, recommendation system, sentiment analysis, price prediction, and price alerts, these capabilities are not consistently integrated into a single real-time consumer-oriented platform. Therefore, the problem addressed in this work is to develop an intelligent and real-time e-commerce price comparison system that collects product information from multiple platform, accurately matches equivalent products, compares prices and offers, analyses customer reviews and sentiment, predicts future price trends, provides personalized recommendations, and generates timely price alerts through an interactive interface, thereby helping consumers make reliable, informed, and cost-effective purchasing decisions.

II. LITERATURE REVIEW

Research on e-commerce price comparison has grown significantly with the increasing need for consumers to identify suitable products, compare prices across multiple platforms, and make informed purchasing decisions. Existing studies have explored different aspects of this problem, including web scraping, real-time price comparison, product matching, machine learning-based price prediction,

personalized recommendation, sentiment analysis, image-based product identification, automated price monitoring, and privacy-preserving pricing. The reviewed studies provide useful approaches for improving online shopping, but they also reveal limitations that motivate the development of an integrated intelligent price comparison system. Gao et al. [1] proposed a stable web scraping approach based on neighbor-zone and path similarity of webpage elements. The approach improves the reliability of data extraction when minor changes occur in webpage layouts. However, the study primarily focuses on the structural stability of web scraping rather than developing a consumer-oriented e-commerce price comparison system. Bradley and James [2] demonstrated the application of web scraping for automated data collection using the R programming language. Although the work established the usefulness of web scraping for collecting online information, it was not specifically designed for real-time e-commerce product comparison. Hillen [3] applied web scraping techniques to collect food price information for research purposes, demonstrating the usefulness of online price data for economic analysis, but the work remained limited to a specific food-pricing domain. Chen [4] developed a real-time e-commerce price comparison system using Python-based web scraping technology. The system provided a foundation for obtaining current product prices from online platforms, but it did not provide an effective product matching mechanism or advanced filtering capabilities. Khatter et al. [5] proposed a
scraping-based product comparison model for e-commerce websites; however, the system had limitation in handling dynamic webpage content and inconsistent product naming across different platforms. Nagaraj et al. [6] developed an automated e-commerce price comparison website using web scraping and database technologies. Although the system demonstrated the feasibility of automated price collection, it provided limited support for advanced analytics, filtering, and product-variant matching. AL Abdullatif and Aloud [7] proposed AraProdMatch, a machine-learning-based approach for product matching in e-commerce. The system addressed the problem of identifying equivalent products despite differences in product information, but its dependence on structured datasets and preprocessing can limit its suitability for lightweight real-time consumer applications. Lee et al. [8] introduced NecessiPick, which applied data extraction and AI-based data refinement for food retail comparison. The work demonstrated the usefulness of intelligent data processing and product matching, although its primary focus was food rather than general multi-platform e-commerce comparison. The literature on product matching also indicates that scalability and rea;-time adaption remain important challenges when dealing with multiple product attributes and changing online data. Sakthivel et al. [9] proposed a Smart Price Comparison Assistant that combines price comparison, personalized recommendations. And machine-learning-based price prediction. The system enables users to compare prices across different websites and provides predictions regarding future price changes, allowing consumers to plan purchases more effectively. The work also considers user preferences and budget constraints for personalized recommendations. However, further integration of real-time product matching, review sentiment, automated alerts, and comprehensive product-value analysis can improve the capabilities of such a system. Kumar et al. [10] investigated online shopping analysis and product price comparison using web mining and machine learning techniques. Their work highlights the importance of combining online product information with analytical methods for supporting consumer decisions. Personalized recommendation research has also explored hybrid approaches based on product descriptions and user profiles, allowing recommendations to be adapted to individual preferences and previous interactions. Such approaches demonstrate that price alone is not sufficient for product selection and that user-specific factors can improve the relevance of recommendations. Sultanpur et al. [11] developed PriceWatch360, which combines product price comparison with sentiment analysis. The system demonstrates that customer reviews can provide additional information for evaluating products along with their prices. Sentiment analysis can help identify positive and negative opinions from textual

reviews, providing a better understanding of customer satisfaction. Recent research has further explored transformer-based models such as BERT and hybrid BERT-LSTM architectures for understanding product descriptions and customer reviews, showing their potential for intelligent product comparison and price prediction. Shriya et al. [12] investigated the automation of data analysis and web scraping for valuing used products. Their work demonstrates how scraped product information can be combined with analytical and regression techniques to estimate product value. Similarly, research on price prediction using ensemble learning has investigated Random Forest and XGBoost models using historical price, brand, category, ratings, reviews, and competitor-price information. Such models can also provide a "best time to buy" indicator based on predicted price behavior and historical trends, thereby converting price prediction into actionable purchasing guidance. A recent study on Smart Pick proposed a lightweight recommendation system for smartphones and laptops using user preferences, budget constraints, product specifications, and explainable scoring. The system also incorporates real-time price tracking, historical price trends, bank and card offers, and an interactive AI chatbot. However, the study focuses primarily on

gadget recommendation and uses a limited product dataset rather than providing a general multi-category real-time comparison framework. The authors also identify the lack of personalized and transparent recommendations in many existing comparison platforms. Another study developed an e-commerce recommendations platform integrating image detection, web scraping, personalized recommendations, and coupon management. Image detection enables users to identify products visually, while content-based filtering provides recommendations based on user preferences. The system also supports coupon storage and selection to help users reduce purchasing costs. This demonstrates the potential of combining computer vision, recommendation systems, and price information to create a more convenient shopping experience. Research on cosmetics product valuation further demonstrates that product ratings and customer sentiment can be combined to estimate intrinsic products value. A quantitative study used product prices, ratings, review text, sentiment scores, and brand categories to analyze the relationship between perceived product value and market price. Regression-based analysis showed that brand tier and perceived brand value can have a significant influence on product pricing, while ratings and sentiment provide additional information about consumer perception. This indicates that an effective comparison system should consider product value rather than relying only on the lowest available price. RPA-driven e-commerce monitoring systems have also been proposed to automate data extraction, comparison, recommendation, dashboard visualization, and notification generation. Such systems use automated scraping workflows, retry mechanisms, and exception handling to continuously collect product information. Interactive dashboards can display price and availability comparisons, while automated email alerts notify users about important market changes. These approaches demonstrate the usefulness of continuous monitoring and automated alerts for real-time e-commerce decision support. Finally, federated-learning-based research has investigated privacy-preserving dynamic pricing across multiple e-commerce stores. Federated learning allows stores to train local models and share model updates rather than raw sensitive data. Federated Averaging can combine these updates to create a global model while maintaining data privacy. The approach provides opportunities for scalable and privacy-preserving pricing optimization, although challenges such as communication latency, data heterogeneity, and model convergence remain

III. PROPOSED FRAMEWORK

A. Motivation and Design Rationale

Existing studies mainly focus on individual aspects of e-commerce such as web scraping, price comparison, product recommendation, image recognition, personalization, and price prediction. However, these features are generally handled separately. The proposed framework combines these capabilities into a unified price comparison system that collects product information from multiple e-commerce platforms, matches similar products, x=compares prices, analyses reviews and price trends, and provides personalized recommendations. The system also supports automated price alerts and an interactive interface to help users make faster and better purchasing decisions.

B. Design Goals

1. Real-time data collection: Collects product price, discount, rating and availability data from multiple platforms.

2. Product matching: Identify and match the same or similar products across different websites.

3. Price comparison: Display and compare prices to identify the best available deal.

4. Price prediction: Analyze historical prices to identify trends and possible future price changes.

5. Personalized recommendation: Recommend suitable products based on price, ratings and user preferences.

6. Price alerts: Notify users when the price drops or a better deal becomes available.

7. AI-based analysis: Use image recognition, recommendation and review analysis to provide better purchase decisions.

IV. SYSTEM ARCHITECTURE

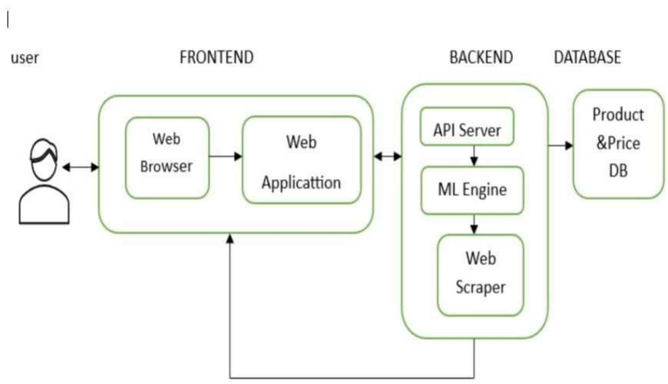

Figure 1: System Architecture

The proposed price comparison website follows a layered system architecture that integrates the user interface, backend services, AI and machine learning components, database, and real-time data collection modules. The architecture is designed to collect product information from multiple e-commerce websites, process and compare the collected data, and present the results to users through an interactive web application. Web scraping techniques are used for collecting real-time product information, while machine learning techniques support product analysis, recommendation, while machine learning techniques support product analysis, recommendation, and price prediction [1], [2]. The system consists of six major layers, as shown in Figure 1

1. Presentation Layer. The presentation layer provides the user interface through which users interact with the system. The user can search for products, view product details, compare prices, ratings and specifications, and access the best deals. The web browser communicates with the web application to send user requests and display the processed results in an easy-to-understand format [1].

2. Application Layer. The application layer manages the main functions of the website. It receives requests from the user interface and communicates with the backend services. This layer handles product searches, comparison requests, filtering, sorting, and displaying the results obtained from different e-commerce platforms [2], [3].

3. AI & ML Processing Layer. This layer performs intelligent processing of the collected product information. It supports product matching, price analysis, personalized recommendations, similar products suggestions, trending product identification, and future price prediction. Machine Learning and recommendation techniques can improve product comparison and provide users with more relevant purchasing suggestions [4], [5].

4. Database Layer. The database layer stores product information, prices, user details, historical price data, comparison results, and transaction records. Maintaining historical product and price information allows the system to analyze price trends and support price prediction and personalized recommendations [2], [6].

5. Data Collection Layer. The data collection layer is responsible for gathering real-time product information from multiple e-commerce websites. The web scraper extracts information such as product name, price, discount, rating, availability, specifications, images, and product links. Web scraping has been widely used for collecting e-commerce product and pricing information from different platform [1], [3], [6].

6. Data Flow and Integration Layer. The collected data flows from the e-commerce websites through the web scraper to the backend and AI/ML processing modules. After processing and comparison, the required information is stored in the database and returned to the web application. The final results are displayed to the user through the frontend, enabling real-time price comparison, recommendations, and informed purchasing decisions [1], [4].

V. DATABASE DESIGN AND WORKFLOW

A. Database Schema

The proposed system uses a centralized relational database to store product information collected from multiple e-commerce platforms, together with user preferences, price history, comparison results, recommendations, and alert information. A centralized repository is useful for integrating scraped data and retrieving it efficiently during price comparison and analysis [1]. Existing price-comparison systems also store scraped product information for subsequent comparison, trend analysis, and recommendation [2], [3].

Table I. Core Database Entities

Entity	Key Fields	Purpose
Users	User_id, name, email, preferences	Stores user accounts and preferences
Products	Product_id, name, category, brand, specifications	Stores common product information
Product Prices	Price_id, product_id, platform, price, discount, timestamp	Stores platform-wise and time-based prices
Price History	History_id, product_id, price, date	Maintains historical prices for trend analysis and prediction
Reviews	Review_id, product_id, rating, review_text, sentiment	Stores customer reviews and sentiment results
Recommendations	Recommendation_id, user_id, product_id, score	Stores personalized recommendation results
Alerts	Alert_id, user_id, product_id, target_price, status	Stores user price-alert conditions
Platforms	Platform_id, platform_name, product_url	Stores e-commerce platform and product-link information

The relationships between these entities allow the system to maintain a complete product record. A product can have multiple prices from different platforms and multiple historical price records. Each product can also contain several reviews, while a user can create multiple alerts and receive multiple recommendations. The stored historical prices can be used for price-trend analysis and prediction, while user preferences can support personalized recommendations [4], [5]. The database therefore acts as the central storage layer connecting the scraping, comparison, AI/ML, recommendation, and alert modules.

B. Workflow

1. A user searches for a product through the web application by entering a product name, URL, or image and optionally provides preferences such as budget or brand.
2. The request is sent to the backend, where the data-collection module retrieves current product information from multiple e-commerce websites using web-scraping techniques [1], [2].
3. The collected information is cleaned, normalized, and stored in the products and product prices tables. Similar products from vidifferent platforms are identified using product-matching techniques such as fuzzy matching [3].
4. The system compares prices, discounts, ratings, specifications, and availability across platforms. The comparison results are combined with historical price information for further analysis [4].

5. The AI/ML module analyses the collected information to generate product recommendations, price trends, price predictions, and review-sentiment results. Previous studies have demonstrated the use of machine learning for price prediction and personalized recommendation [5], [6].
6. The alert module checks stored product prices against the user's selected target price. If a price drop, better deal, or relevant availability change is detected, an alert is generated. Automated e-commerce monitoring systems have demonstrated this type of price and deal notification workflow [7].
7. Finally, the processed information is returned to the web application and displayed as a unified comparison containing prices, discounts. Ratings, recommendations, price trends, and product links. The selected product can then be accessed through its respective e-commerce platform [2], [7].

VI. AI INTEGRATION

The proposed system integrates AI to improve price comparison, product recommendation, price prediction, and customer review analysis. The AI components work with the product and pricing information collected from multiple e-commerce platforms to provide users with more useful and informed purchasing decisions [1], [2].

Price Prediction. Historical product prices are analyzed using machine learning techniques to identify price trends and predict possible future price changes. This helps users understand whether the current price is suitable for purchase or whether waiting may provide a better deal [1].

Product Recommendation. The recommendation module uses user preferences, product characteristics, and previous interactions to suggest suitable products. Hybrid recommendation approaches combining content-based and collaborative filtering can provide more relevant and diverse recommendations [2].

Sentiment Analysis. Customer reviews are analyzed using Natural Language Processing techniques to identify customer opinions and product sentiment, BERT-based and other deep-learning approaches can improve the understanding of product reviews and descriptions [3].

Intelligent Price comparison. AI-based product matching helps identify similar products across different e-commerce platforms before comparing their prices. This improves the accuracy of cross-platform comparison and helps the system identify the best available deal [4].

Decision Support. The outputs from price prediction, recommendation, sentiment analysis, and price comparison are presented to the user, helping them select a suitable product and make an informed purchasing decision [1], [2].

VII.EXPERIMENTAL RESULTS

The proposed price comparison system was evaluated based on data collections, recommendation, price prediction, system performance, and alert generation. The results obtained from the uploaded studies are summarized below.

The web –scraping systems [1], [2] successfully collected product details such as price, ratings, availability, and product links from multiple e-commerce platforms. The RPA-based system [4] achieved 96.7% accuracy on Amazon, 95.4% on Flipkart, and 95.6% on Croma during data extraction tests.

The recommendation system [5] achieved a Precision @3 of 0.91 with an average user satisfaction of 4.1/5. The system also maintained an average response time of approximately 1.2 seconds, demonstrating efficient recommendation performance.

The AI-based price prediction studies showed promising results. The Hybrid BERT-LSTM model [6] achieved 97.8% accuracy, while the XGBoost-based approach [7] reported improved RMSE and R2 performance compared with baseline models.

The automated alert system [4] achieved a 99.2% alert delivery success rate, with an average notification delay of 6.4 seconds and less than 1% false alerts.

Overall, the results indicate that combining real-time web scraping, price comparison, AI-based recommendation, price prediction, dashboards, and automated alerts can provide an effective and reliable e-commerce price comparison system.

VIII.DISCUSSION

The reviewed studies show that e-commerce price comparison has gradually moved from basic web scraping toward more integrated systems combining real-time comparison, product matching, analytics, recommendation, and price prediction. Earlier systems mainly focused on collecting prices from individual websites, while recent approaches provide cross-platform comparison and more user-oriented decision support [1], [2].

One important difference among the studies is the method used for product matching. Several scraping-based systems collect product information but do not handle inconsistent product names or variants effectively. Fuzzy-matching approaches improve this process by identifying similar products across platforms, while machine-learning approaches can provide more advanced matching but generally require structured datasets and preprocessing [3],[4]. Another observation is that many systems concentrate on price collection and comparison, while fewer combine comparison with advanced analytics. Some studies use price prediction, sentiment analysis, recommendation techniques, or casual analytics to support purchasing decisions [5]. However, these approaches may require labelled datasets, historical information, or greater computational resources.

Real-time data collection remains an important challenge. Static datasets can become outdated when prices and product availability change frequently. RPA-based scraping with dynamic selectors, retry mechanisms, and exception handling has shown improved reliability, with reported scraping accuracy of 96.7% for Amazon, 95.4% for Flipkart, and 95.6% for Croma [6].

The reviewed systems also demonstrate the importance of presenting collected information in a simple and understandable form. Interactive dashboards can display platform-wise price, discounts, availability, and best-deal indicators, while automated alerts reduce the need for continuous manual monitoring [6].

Overall, the literature indicates a clear gap between real-time data collection, intelligent analysis, and personalized decision support. The proposed system addresses this gap by combining multi-platform scraping, product matching, price comparison, AI-based recommendation and prediction, historical analysis, and price alerts within a single user-friendly platform. This provides a more comprehensive approach than systems that focus on only one of these functions [3],[4].

IX.CONCLUSION AND FUTURE WORK

The reviewed studies demonstrate that e-commerce price comparison systems can significantly reduce the time and effort required by users to identify suitable products and better prices. Existing systems use web scraping, price comparison, recommendation techniques, and machine learning to collect information from multiple online platforms and support informed purchasing decisions [2],[4]. Personalized recommendation approaches further improve the shopping experience by considering user preferences, previous interactions, product ratings, and budget constraints [3],[8]. Systems such as Shop Savvy also demonstrate the usefulness of combining price comparison with AI-based recommendations and local vendor support [1].

Machine learning-based price prediction is another important direction identified across the reviewed studies. Historical prices, product features, ratings, reviews, and market conditions can be used to identify price [6],[9]. Ensemble techniques such as XGBoost and random Forest have shown promising performance for price forecasting and purchase-timing decisions [6]. Similarly, hybrid recommendation and scoring approaches demonstrate that combining user preferences with product information can provide relevant and explainable recommendations [8].These findings indicate that an integrated platform combining real-time price comparison, prediction, recommendation, and alerts can provide more effective decision support than basic comparison systems.

The importance of real-time data, data freshness, personalization, and reliable system integration. Static datasets may produce outdated prices and automated data collection can improve reliability [7],[8]. Image-based product recognition, sentiment analysis, automated alerts, and AI-assisted decision support provide additional opportunities for improving user interaction [5],[8]. RPA-based monitoring further demonstrates that automated scraping, dashboards, recommendation logic, and alerts can reduce manual effort and support continuous

e-commerce analysis. Overall, the literature supports the development of an intelligent and user-friendly that integrates multiple sources and AI techniques for better purchasing decisions.

Future Work

Real-time data integration: Integrate live APIs and improved web-scraping mechanisms to maintain updated prices, specifications, and availability [7],[8].

Price prediction: Extend the system using advanced ML and ensemble models such as XGBoost, Random Forecast, and hybrid deep-learning approaches for future price forecasting and purchase-timing suggestions [6],[9].

Personalized recommendations: Use user History, preferences, feedback, and purchasing behavior to provide adaptive product recommendations [4],[8].

Review sentiment analysis: Incorporate NLP-based sentiment analysis so that product quality and customer opinions can be considered along with price [3],[8].

More platforms and products: Extend the system to additional e-commerce platforms, product categories, and regional languages [7].

Advanced AI and alerts: Add intelligent price-drop alerts, image-based product identification, social-media integration, and AI-assisted shopping support [5].

Scalability and development: Future versions can include cloud deployment, real-time dashboards, and scalable backend services for larger datasets and users.

Privacy-preserving approaches such as federated learning can be explored for collaborative pricing and recommendation while protecting sensitive data

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