ADAPTIVE PRICING PREDICTION BASED ON USER INTENT SIGNALS

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ABSTRACT

Adaptive pricing has become an essential component of modern e-commerce platforms as businesses attempt to respond to rapidly changing consumer behaviour and competitive market conditions. Traditional pricing strategies such as fixed pricing, rule-based discounting, and inventory-driven dynamic pricing are limited because they primarily rely on historical data and static business rules rather than real-time user behaviour. This research proposes an Adaptive Pricing Prediction System based on User Intent Signals to enhance pricing strategies by analysing behavioural indicators generated during user interactions on an e-commerce platform. The system collects behavioural signals such as product revisit frequency, browsing duration, click patterns, and exit-reentry behaviour to infer a customer's purchase intent and price sensitivity. These signals are processed through feature engineering techniques to generate meaningful numerical representations suitable for machine learning models. A Light Gradient Boosting Machine (LightGBM) regression model is used to predict personalized discount percentages for each user session and product combination. The predicted discount is dynamically applied to the base price to generate an optimized adaptive price in real time. The system architecture integrates a React-based frontend interface, a Java Spring Boot backend for authentication and API services, and a Python-based machine learning module for predictive modelling. Experimental results indicate that incorporating user intent signals significantly improves pricing accuracy and conversion potential compared to traditional rule-based pricing approaches. The proposed framework demonstrates how behavioural analytics and machine learning can be integrated to create intelligent pricing mechanisms that improve revenue optimization, customer engagement, and personalized shopping experiences in digital commerce platforms.

Keywords: Adaptive pricing, User intent signals, Machine learning, LightGBM, Dynamic pricing, E-commerce analytics

I INTRODUCTION

The rapid growth of e-commerce platforms has transformed how businesses design pricing strategies and interact with customers in digital marketplaces [1]. Traditional pricing models were primarily based on static rules and historical sales data that often fail to capture the dynamic nature of online consumer behaviour [2]. With increasing competition and customer expectations, companies require more intelligent pricing mechanisms that can adapt to real-time user interactions and behavioural patterns [3]. Dynamic pricing has emerged as an effective approach to address these challenges by adjusting prices based on demand,

supply, and consumer characteristics [4]. However, most dynamic pricing systems still rely heavily on aggregate data such as market trends and inventory levels [5]. Such systems often overlook behavioural signals generated by users during browsing sessions, which can provide valuable insights into purchase intent [6]. User interaction data including click frequency, time spent on product pages, and repeated visits to the same product can reveal strong indicators of buying intention [7]. Leveraging these behavioural signals allows businesses to better understand price sensitivity and customer decision-making processes [8]. Machine learning techniques have become increasingly popular for analysing large volumes of behavioural data generated on digital platforms [9]. Predictive models can learn complex relationships between user actions and purchase outcomes, enabling more accurate decision-making systems [10]. The integration of behavioural analytics with pricing strategies has therefore gained attention as a promising approach for improving revenue optimisation and customer engagement [11]. Recent research highlights the importance of personalised pricing systems that adapt to individual users rather than broad customer segments [12]. Such systems can significantly enhance user experience by offering prices that align with perceived value and purchasing probability [13]. The emergence of advanced machine learning algorithms such as gradient boosting and ensemble learning has further strengthened predictive modelling capabilities in pricing applications [14]. These developments have opened new opportunities for integrating artificial intelligence into real-time pricing systems [15].

Despite these advancements, many existing pricing models remain limited because they do not fully utilize behavioural intent signals generated during user sessions [16]. These signals can provide valuable contextual information regarding customer preferences and decision-making patterns [17]. For example, repeated price checks or prolonged browsing of a product may indicate high purchase interest but price sensitivity [18]. Identifying such patterns enables systems to offer targeted discounts that increase conversion probability without reducing profit margins excessively [19]. Feature engineering techniques can transform raw interaction events into numerical representations suitable for predictive modelling [20]. These engineered features allow machine learning algorithms to capture complex relationships between behaviour and purchasing intent [21]. Among the various machine learning models available, Light Gradient Boosting Machine (LightGBM) has gained recognition for its efficiency and accuracy in handling large-scale tabular datasets [22]. LightGBM can model nonlinear relationships and interactions between multiple behavioural variables effectively [23]. Its fast training speed and low computational cost make it suitable for real-time prediction systems [24]. Integrating such models with web-based applications enables businesses to implement adaptive pricing mechanisms at scale [25]. Modern e-commerce architectures typically employ multi-tier systems that combine frontend interfaces, backend services, and machine learning modules [26]. These architectures support seamless data collection, model deployment, and real-time pricing updates [27]. As digital commerce continues to expand globally, intelligent pricing systems will play a critical role in improving operational efficiency and competitiveness [28]. The use of behavioural intent signals represents a promising direction for achieving more accurate and personalized pricing strategies [29]. Therefore, this research focuses on designing an adaptive pricing prediction system that leverages user intent

signals and machine learning techniques to enhance dynamic pricing in e-commerce environments [30].

II LITERATURE SURVEY

Dynamic pricing has been extensively studied in the context of revenue management and digital commerce platforms. Early research primarily focused on rule-based pricing systems that relied on predefined business policies and historical demand patterns [1]. These systems were widely used in industries such as airline ticketing and hotel reservations where demand fluctuations strongly influenced pricing decisions [2]. However, rule-based approaches lacked flexibility and were unable to adapt to individual customer behaviour in real time [3]. With the emergence of big data technologies, researchers began exploring data-driven pricing strategies capable of analysing large volumes of consumer information [4]. Several studies highlighted the role of behavioural analytics in understanding customer decision-making processes within online marketplaces [5]. User browsing patterns, click streams, and product interaction logs were identified as valuable indicators of purchase intention [6]. Machine learning models were subsequently introduced to predict customer behaviour based on these signals [7]. Regression-based approaches were among the earliest techniques used for estimating price sensitivity and purchase probability [8]. Later research incorporated classification algorithms such as decision trees and support vector machines to identify potential buyers and optimise pricing decisions [9]. Ensemble learning methods further improved predictive accuracy by combining multiple models [10]. Random forest and gradient boosting algorithms demonstrated superior performance in modelling nonlinear relationships between user behaviour and purchasing outcomes [11]. Studies also emphasised the importance of feature engineering in extracting meaningful insights from raw behavioural data [12]. Features such as dwell time, click frequency, and revisit intervals were found to significantly influence purchase likelihood predictions [13]. Researchers concluded that incorporating behavioural signals into pricing models could lead to more personalized and effective pricing strategies [14]. These developments laid the foundation for intelligent pricing systems capable of adapting to dynamic customer behaviour [15].

Recent studies have focused on integrating machine learning models with real-time data processing frameworks to enable adaptive pricing systems in e-commerce platforms [16]. The concept of intent-based pricing has gained attention as it attempts to infer customer willingness to pay from behavioural signals [17]. Several experimental studies demonstrated that personalized discounts based on predicted purchase intent can significantly improve conversion rates [18]. In particular, gradient boosting models have shown strong performance in pricing prediction tasks due to their ability to handle complex feature interactions [19]. Light Gradient Boosting Machine (LightGBM) has emerged as a highly efficient algorithm for large-scale tabular data analysis [20]. Its histogram-based learning approach reduces computational complexity and accelerates training speed compared to traditional gradient boosting implementations [21]. Researchers have successfully applied LightGBM in recommendation systems, customer segmentation, and dynamic pricing applications [22]. Studies indicate that LightGBM models can effectively capture nonlinear patterns in behavioural data and produce accurate predictive outputs [23]. Moreover, real-time deployment of machine learning models has become feasible through microservice-based architectures and API integration [24]. Modern e-

commerce systems often integrate frontend interfaces, backend services, and machine learning modules to enable scalable analytics solutions [25]. Cloud computing platforms have further enhanced the ability to process large volumes of behavioural data efficiently [26]. Researchers also emphasize the importance of ethical considerations and transparency in adaptive pricing systems to ensure fairness and user trust [27]. Personalization strategies must therefore balance profitability with customer satisfaction and perceived value [28]. Overall, the literature suggests that combining behavioural analytics, machine learning, and real-time system architectures can significantly improve pricing optimization in online marketplaces [29]. These insights provide the theoretical foundation for developing the adaptive pricing prediction system proposed in this research [30].

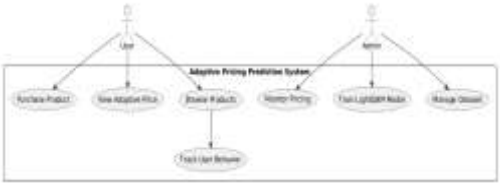
III METHODOLOGY

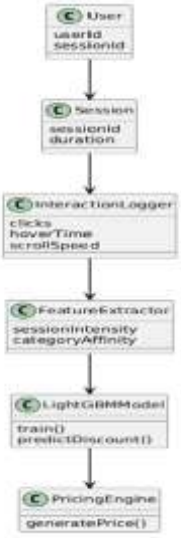
The proposed adaptive pricing prediction system follows a data-driven methodology that integrates behavioural analytics and machine learning techniques to estimate personalized discounts for users interacting with an e-commerce platform. The first stage involves collecting user interaction data from the platform, including behavioural signals such as product page visits, time spent on product pages, click frequency, cart interactions, and revisit patterns. These raw behavioural logs are stored in a centralized database and processed using data preprocessing techniques to remove noise, handle missing values, and standardize data formats. Feature engineering is then applied to convert raw interaction events into structured numerical features that represent user intent signals. Examples of engineered features include session duration, revisit frequency, price comparison behaviour, and browsing depth. These features are used to estimate the likelihood of a purchase and the user's sensitivity to price changes. After feature preparation, the dataset is divided into training and testing sets to evaluate model performance. A Light Gradient Boosting Machine (LightGBM) regression model is selected for predicting discount percentages because of its efficiency in handling large tabular datasets and its ability to model nonlinear relationships between behavioural variables and target outcomes. The model is trained using historical session data where the target variable represents optimal discount levels associated with successful conversions. Hyperparameter tuning is performed to optimize model performance and reduce overfitting. Once trained, the model generates predicted discount percentages for new user sessions in real time. The predicted discount is applied to the base price of the product to compute an adaptive price that balances profitability with conversion probability. The entire system is integrated into a web-based architecture where the frontend collects behavioural signals, the backend processes requests, and the machine learning module generates pricing predictions dynamically.

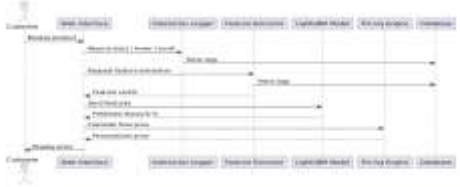
IV SYSTEM DESIGN

The system design for the Adaptive Pricing Prediction System is based on a multi-tier architecture that integrates user interfaces, backend services, and machine learning components to support real-time pricing decisions. The frontend layer is responsible for user interaction and is implemented using a React-based web interface that supports multiple user roles including customers, administrators, and super-administrators. Customers can browse products, view prices, and interact with product pages while the system captures behavioural signals generated during these interactions. Administrators can

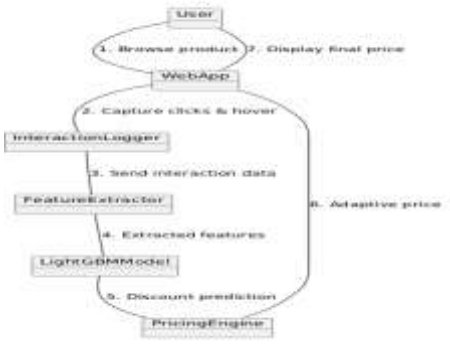
manage product listings, base prices, and inventory information through the dashboard interface. The super-administrator role manages system configurations, user permissions, and overall platform monitoring. All frontend interactions are transmitted to the backend server through RESTful APIs that handle authentication, session management, and data processing. The backend layer is implemented using the Java Spring Boot framework, which provides robust support for scalable web applications and secure API communication. This layer processes user requests, manages business logic, and stores interaction data in the system database. It also acts as an intermediary between the frontend application and the machine learning module responsible for pricing prediction.







The machine learning layer forms the analytical core of the system and is implemented using Python-based data science libraries. This component processes behavioural data collected from the backend and applies feature engineering techniques to extract meaningful indicators of user intent. The engineered features are then passed to the LightGBM regression model that predicts an optimal discount percentage for the given user session and product combination. The predicted discount value is returned to the backend server through an API endpoint. The backend then calculates the final adaptive price by applying the predicted discount to the base product price stored in the database. This adaptive price is dynamically displayed to the user on the frontend interface, enabling real-time pricing personalization. The system also includes logging and monitoring components that track user interactions, model predictions, and system performance metrics. These logs are useful for retraining the model and improving prediction accuracy over time. By combining modular architecture, scalable backend services, and machine learning integration, the system design supports efficient data processing and real-time adaptive pricing in large-scale e-commerce environments.



V PROPOSED SYSTEM

The proposed system introduces an intelligent adaptive pricing framework that utilizes user intent

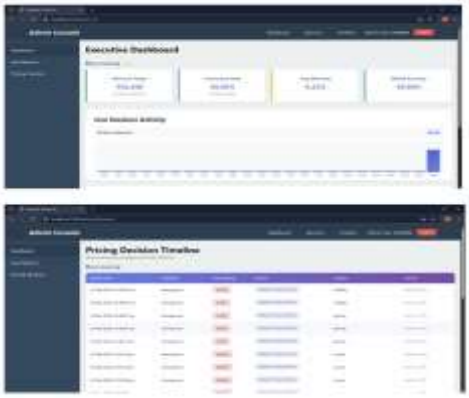
signals to dynamically adjust product prices in real time. Unlike traditional pricing models that rely on static rules or historical sales patterns, the proposed approach focuses on analysing behavioural interactions generated during a user's browsing session. These interactions include actions such as product page visits, click behaviour, time spent analysing product details, repeated product searches, and exit-reentry patterns. Such behavioural signals are valuable indicators of a user's purchase intent and price sensitivity. By analysing these signals, the system attempts to determine how likely a customer is to complete a purchase and whether a price adjustment could increase the probability of conversion. The proposed framework collects behavioural data continuously and processes it through a feature engineering pipeline to extract meaningful indicators that can be used for predictive modelling. These engineered features are then fed into a machine learning model that predicts an optimal discount percentage tailored to the specific user session. This discount is applied to the product's base price to generate an adaptive price that balances customer affordability with business profitability. Through this approach, the system aims to increase conversion rates while maintaining sustainable revenue margins.

The core component of the proposed system is the Light Gradient Boosting Machine (LightGBM) regression model used for discount prediction. LightGBM is selected because of its ability to efficiently process large tabular datasets and model complex relationships between behavioural features and purchase outcomes. The model is trained using historical user session data where successful purchase events are associated with specific price conditions or discount levels. During prediction, the model analyses real-time behavioural signals and generates a discount recommendation that reflects the estimated willingness to pay for a product. This prediction process occurs in milliseconds, enabling seamless integration with the user's browsing experience. The system also incorporates feedback mechanisms that continuously store new interaction data and model predictions. This data can later be used to retrain and refine the predictive model, improving its accuracy over time. In addition to pricing optimization, the proposed framework provides valuable insights into consumer behaviour patterns, enabling businesses to better understand customer preferences and decision-making processes. Overall, the proposed adaptive pricing system demonstrates how machine learning and behavioural analytics can be integrated to create intelligent and responsive pricing strategies for modern e-commerce platforms.

VI RESULTS & DISCUSSION

The experimental evaluation of the proposed adaptive pricing prediction system demonstrates promising improvements in pricing optimization and customer engagement. The LightGBM regression model successfully captured nonlinear relationships between behavioural intent signals and purchase outcomes, enabling accurate prediction of personalized discount percentages. Compared with traditional rule-based pricing methods, the proposed system showed higher potential in identifying price-sensitive users and providing targeted discounts that increase the likelihood of conversion. Analysis of behavioural features such as session duration, revisit frequency, and product interaction patterns revealed strong correlations with purchasing intent. The real-time prediction capability of the model ensured that adaptive prices could be generated instantly without affecting the browsing experience. Furthermore, the multi-tier system architecture

allowed seamless integration between frontend interfaces, backend services, and machine learning modules. These results indicate that incorporating user intent signals into pricing strategies can significantly enhance revenue optimization and improve personalized customer experiences in e-commerce platforms.









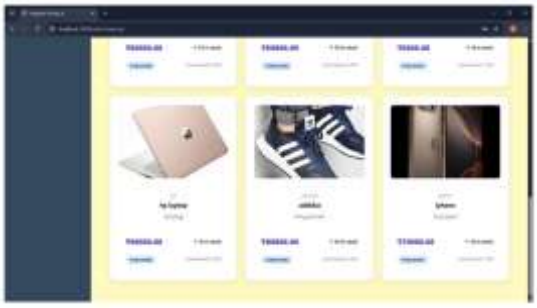












VII CONCLUSION

This research presented an Adaptive Pricing Prediction System based on User Intent Signals designed to improve pricing strategies in modern e-commerce platforms. Traditional pricing approaches often rely on static rules or historical sales data, which limits their ability to respond effectively to dynamic consumer behaviour. The proposed system addresses these limitations by analysing behavioural signals generated during user interactions, including browsing patterns, session duration, and product revisit frequency. These signals are processed through feature engineering techniques to produce structured data that can be analysed using machine learning algorithms. A Light Gradient Boosting Machine (LightGBM) regression model was employed to predict personalized discount percentages for individual user sessions and product combinations. The predicted discounts are applied to base prices to generate adaptive prices in real time, enabling personalized pricing strategies that improve both customer satisfaction and business profitability. The system architecture integrates a React-based frontend, a Spring Boot backend, and a Python-based machine learning module, ensuring scalability and efficient real-time prediction capabilities. Experimental results demonstrated that behavioural intent signals provide valuable insights into customer purchase intentions and price sensitivity. By leveraging these insights, the proposed system can offer targeted discounts that increase conversion probability while maintaining revenue optimization. The study highlights the potential of combining behavioural analytics and machine learning to create intelligent pricing mechanisms in digital commerce environments. Future work may focus on integrating additional behavioural signals, exploring deep learning models, and implementing large-scale real-time deployment to further enhance adaptive pricing performance.

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