Journal of Organizational and End User Computing
Volume 37 • Issue 1 • January-December 2025

Optimization of Dynamic Pricing Models for Consumer Segmentation Markets and Analysis of Big Data-Driven Marketing Strategies

Qi Zhang
Anhui International Studies University, China

Qiang Shi
https://orcid.org/0009-0002-0933-7809
Anhui International Studies University, China

Bilal Alatas
https://orcid.org/0000-0002-3513-0329
Firat University, Turkey

Yu-His Yuan
National Taiwan University of Arts, Taiwan

ABSTRACT

In response to the challenges posed by globalization and rapid technological advancements, traditional static pricing models are no longer sufficient to capture the dynamic nature of consumer behavior and market fluctuations. This study proposes a "Multi-dimensional Dynamic Pricing Optimization and Consumer Behavior Prediction Model Driven by Big Data," which integrates multi-source data and reinforcement learning to improve dynamic pricing strategies. Through a hybrid model architecture using Random Forest and LSTM, it captures both static and time-series features. Experimental results show that the proposed model significantly outperforms baseline models, achieving a 43% reduction in Mean Squared Error (MSE), a 28% decrease in Mean Absolute Percentage Error (MAPE), a 6.5% increase in Accuracy, and a 14.7% increase in Cumulative Revenue. These findings confirm the model's ability to enhance prediction accuracy, optimize pricing strategies, and maximize revenue, demonstrating its potential for real-world applications in industries like e-commerce, finance, and advertising.

KEYWORDS

Dynamic Pricing, Consumer Behavior Prediction, Reinforcement Learning, Multi-Source Data Integration, Real-Time Strategy Optimization

INTRODUCTION

In the context of rapid globalization and the swift development of the internet, market competition has become increasingly fierce, posing new challenges for companies in formulating effective pricing strategies (Alon et al., 2020). Traditional static pricing models, which rely heavily on historical data and fixed rules, have proven insufficient in addressing the dynamic and rapidly changing nature of the market and consumer behavior (Kopalle et al., 2023). With the rapid advancements in big data

DOI: 10.4018/JOEUC.368840

and artificial intelligence, dynamic pricing has emerged as a promising solution. Dynamic pricing adjusts prices in real time to maximize profits and enhance customer satisfaction and has garnered widespread attention for its potential to optimize revenue in fluctuating market conditions (Gazi et al., 2024).

The effectiveness of dynamic pricing is heavily reliant on the ability to accurately predict consumer behavior and swiftly respond to market changes (Alamdar & Seifi, 2024). However, traditional approaches to pricing often rely on a limited range of data sources, such as historical sales data, or use simple models, such as linear regression or rule-based systems, which are inadequate for processing the complex, multidimensional, and unstructured data that increasingly shape consumer behavior (Antol et al., 2021). This limitation results in pricing strategies that fail to adequately capture and respond to the nuanced and ever-evolving needs and preferences of consumers.

To address these challenges, this study proposes a multidimensional dynamic pricing optimization and big data–driven consumer behavior prediction model." The core innovation of this model lies in its ability to integrate multiple heterogeneous data sources, including structured data (e.g., historical sales and inventory), unstructured data (e.g., user reviews and social media content), and behavioral data, to conduct comprehensive feature extraction and build a high-quality, robust feature set. This integration allows for a more complete and accurate understanding of consumer behavior, which significantly enhances the predictive power of the dynamic pricing model.

Furthermore, the study leverages deep learning techniques, such as long short-term memory (LSTM) networks, to capture time series features and model the temporal dynamics of consumer behavior. By combining these deep learning methods with ensemble learning models, such as random forest (Jin et al., 2024), the model is able to process multidimensional structured data and perform feature selection and classification tasks with improved precision. This hybrid model approach not only improves predictive accuracy but also enhances the model's capacity to identify complex behavioral patterns, surpassing the capabilities of traditional pricing models.

Finally, reinforcement learning (RL) algorithms are incorporated to optimize pricing strategies in real-time. The RL mechanism allows the model to dynamically adapt to market changes through continuous interactions with the market environment. This adaptive learning process enables the model to refine its pricing decisions over time, achieving both long-term profit maximization and improved customer satisfaction (Kastius & Schlosser, 2022).

The model development process involves the preprocessing and feature extraction of multiple data sources, transforming structured data (such as price and sales) and unstructured data (such as user reviews and social media content) into unified feature vectors. These vectors are then standardized and normalized, ensuring consistency and compatibility. The hybrid architecture enables the model to precisely predict consumer behavior and, through RL, continuously optimize pricing strategies, allowing it to adjust and learn in real time within dynamic market environments.

The main contributions of this study are as follows:

- Comprehensive integration of multiple heterogeneous data sources. This study is the first to fully integrate historical sales, user behavior data, and social media data into a dynamic pricing model, providing a comprehensive view of consumer behavior and significantly improving prediction accuracy.
- Development of a high-precision consumer behavior prediction model. By using LSTM networks to model time series data and combining them with ensemble learning models, such as random forest, for feature selection and classification, the study significantly improves the ability to identify complex consumer behaviors, outperforming traditional approaches.
- Incorporation of RL for real-time pricing optimization. The inclusion of RL enables the model to optimize pricing strategies dynamically, responding to market fluctuations in real time and enhancing the robustness and effectiveness of pricing decisions.