Product Bundling Recommendations for e-Commerce Using Machine Learning Techniques

Adriana Syaffiya Ahmad Khadri1, a), Su-Cheng Haw1, 2, b), Elham Anaam1, c) and Lucia D. Krisnawati3, d)

1Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Malaysia.

2Center for Digital Innovations, CoE for Immersive Experience, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Malaysia  
 3Faculty Information Technology, Universitas Kristen Duta Wacana, Yogyakarta, Indonesia.

b)Corresponding author: sucheng@mmu.edu.my

a)1191200471@student.mmu.edu.my

c) anaamelham@gmail.com

d) krisna@staff.ukdw.ac.id

**Abstract.** The demand for product bundling continues to grow among e-commerce businesses because it produces better customer satisfaction and higher sales outcomes. The traditional bundling methods rely on static rules and opinions of experts to bundle, which may not fully capture the current customer’s behavior and purchasing trends. This research develops a machine learning (ML) based product bundling recommendation system to improve the bundled products on sale in the e-commerce electronics sector. The customer purchase patterns are analyzed using three ML techniques, namely, Decision Trees (DT), K-Nearest Neighbors (KNN) and Association Rule Mining (ARM), and data-driven bundling recommendations are generated. The DT are structured, rule based bundling models, the KNN is based on proximity of features used to identify similarities amongst products, and the ARM is based on the use of support, confidence, and lift metrics to detect association patterns. To ensure personalized and optimized bundling recommendations, the system is evaluated using accuracy, precision, recall, and lift. This data-driven approach helps with improving customer engagement and inventory management and gives more chances of cross-sales. Additionally, the suggested system is designed to be scalable and flexible, allowing it to keep developing along with the changes in users’ behaviors and the development of market trends. This research contributes to the advancement of personalized recommender systems in e-commerce, as it provides an automated and strategic approach to the improvement of product bundling in the e-commerce sector.

# INTRODUCTION

The modern e-commerce environment requires retailers to use product bundling as a fundamental approach for improving customer value and boosting sales [1]. Product bundling exists as a business strategy which combines related products into one package for customers to buy at reduced rates, so customers can gain both convenience and more product options [2],[3]. The traditional bundling systems relieve expert intuition and opinion with static rules that present limited adaptability to consumer demands as well as market trends development. The traditional manual methods produce product arrangements which fail to match the wide range of customer requirements. Traditional manual bundling methods lead to poor product assortment decisions because they fail to recognize the wide range of customer needs [4].

Businesses can overcome bundling challenges thanks to the increasing customer transaction data availability which allows ML advancement to create data-driven strategies [5]. Large-scale purchase history analysis through ML allows the discovery of hidden co-purchase information which enables the development of improved bundled recommendations [6]. The shift from traditional rule-based bundling to ML-powered bundling improves revenue through dynamic adjustable bundles that also produce better customer satisfaction results [7].

ML techniques have proven effective for enhancing personalized product recommendations according to existing research in recommender systems [8],[9],[10]. Recommender systems use collaborative filtering and content-based filtering to recommend products to boost customer engagement and enhance sales according to research findings in [11]. Researchers have applied numerous ML approaches to address the problem of bundle recommendation beyond standalone item suggestions. ARM enables identification of frequently purchased items in transaction data thus generating successful product bundles according to research [12],[13]. The research by Oetama [14] demonstrated how e-commerce association rule mining could identify essential co-purchase patterns in market transactions.

The bundling recommendation uses DT as an alternative method. The DT method breaks down customer groups by buying patterns to produce simple bundle rules [15]. A DT model combined with ARM allowed Wang [8] to evaluate consumer purchase information and create tactics for bundling that boosted customer loyalty and revenue outcomes. KNN presents a method for bundle personalization through customer grouping based on their purchasing behaviors [16],[17]. Putra and Ilmi [18] constructed a KNN-based system to identify customer clusters through which recommended frequently co-bought products with successful precision and recall rates exceeding 83%.

The research explores three ML methods [19],[20] including DT and KNN and ARM to determine its ability in creating product bundling recommendations. The selected techniques represent separate methodological approaches found in ML [21],[22]. The rule-based classifier DT establishes hierarchical decision structures to create interpretable bundling rules because of its modeling capabilities. Collaborative filtering systems use KNN as a similarity-based algorithm to generate personalized bundles through user-item relations in feature space. With its ability to locate robust item relationships based on data transaction history ARM serves as a different pattern mining method from the frequent pattern mining technique. The research benefits from incorporating different bundling approaches which facilitates a complete evaluation of bundle tactics used in e-commerce platforms.

# METHODS

This research investigates three ML approaches including DT, KNN and ARM for product bundling recommendation in the e-commerce sector. The goal is to find the best method to recommend data-driven product bundles based on real customer purchasing patterns. The models are evaluated through individual implementation on identical data followed by standard rule-mining and classification metric assessment. The evaluation process follows consecutive steps to achieve accurate assessments which align with operational e-commerce platforms. Figure 1 illustrates the process of data processing and model training and model performance evaluation.

A diagram of data processing

AI-generated content may be incorrect.

**FIGURE 1.** Overview of the model development and evaluation architecture

The data used is from Amazon Electronics Products Sales dataset from Kaggle. The dataset contains more than 1.2 million records which show user-product interactions along with user IDs and item IDs and product categories and brands and rating values between 1 to 5 and timestamp information. Additional information in the dataset consists of user demographics alongside product features. The dataset provides complete information for both co-purchase behavior detection and product popularity evaluation and transaction pattern discovery for bundling applications.

The data preprocessing process included multiple steps which prepared the modeling inputs to become both clean and meaningful. Preprocessing began with filling missing values in categorical variables such as brand and user fields using custom placeholder values like "Unknown" or "None." The data preprocessing stage included eliminating duplicates while converting timestamp data into datetime type for extracting temporal field information. The categorical features brand, category and model type received label encoding as part of the preprocessing process. New composite features, including category-brand combinations and user average ratings, were engineered to capture more detailed product-user interactions. The classification target consisted of two categories where ratings above 3 received a value of 1 (positive feedback) while ratings at 3 or below received a value of 0. The dataset was then split into 80% training and 20% testing while preserving class distribution. The minority class received additional samples through SMOTE to reduce class imbalance. The Z-score normalization technique was applied to all numeric features because KNN requires it for optimal performance. ARM requires transactional data which was created during preprocessing step by grouping purchases by users over fixed time intervals, filtering transactions with more than one item, and applying one-hot encoding to generate the item basket matrix.

The DT model utilized CART classifier technology for its development. A grid search procedure was conducted to optimize the essential hyperparameters including maximum tree depth and minimum leaf samples and split criteria selection between Gini index and entropy. The tree structure produced rules that showed which product and user attribute combinations resulted in positive feedback. The established rules enabled classification while simultaneously creating a rule-based system for product bundle recommendations. As a result of the interpretability, e-commerce sector can conveniently understand the reasons behind product suggestions which helps make better business decisions.

KNN was used as a collaborative filtering method which provided bundle recommendations through the analysis of product or user similarity. The encoded and scaled dataset transformed each product and user into points that existed within multidimensional space. The KNN model calculated the nearest neighbors through cosine similarity computations. The model determined similar items based on user buying patterns to suggest product combinations which could effectively be grouped together. The experimental determination of “k” value produced the best validation data performance. This approach allows businesses in e-commerce to suggest products together based on what other users with the same preferences have bought.

ARM was employed using the FP-Growth algorithm to extract frequent itemsets from the transactional dataset. The FP-Growth algorithm produced association rules X ⇒ Y which identified common item sets that customer bought together by applying minimum support and confidence thresholds. The evaluation of each rule depended on support, confidence and lift measurements. Bundle candidates were chosen from rules displaying high lift values because it showed superior than random product interdependence. The method revealed hidden co-purchase patterns which traditional bundling methods would overlook. Such patterns are especially helpful for learning about static and promotional bundles that show how real customers shop in large e-commerce settings.

The model performance evaluation relied on classification and rule-mining metrics. DT and KNN received evaluation through accuracy and precision and recall and F1-score metrics. The metrics evaluate how well the model predicts user responses to bundle offers. The quantitative value of correct positive predictions appears as precision whereas recall represents how well the model detects every relevant item. Evaluations are combined through F1-score to provide a unified metric for assessment. ARM utilized support to determine itemset frequency in the dataset while confidence showed the probability of buying item Y after purchasing item X and lift evaluated the association strength through actual co-occurrence versus random chance. Rules that achieved support levels above 0.01 and confidence levels above 0.3 and lift levels above 1.0 were deemed meaningful. The evaluation process involved dual-layered evaluation to guarantee accurate predictions and useful e-commerce bundling.

The evaluation of each approach was implemented independently to determine its effectiveness for e-commerce product bundling. The DT provided rules which described user-item behaviors while ARM discovered important co-buying relations from sales information and KNN generated personalized suggestions through item similarity measures. Comparative analysis method helped identify the advantages and weaknesses of these approaches when dealing with static bundling issues. The evaluation findings led to the selection of the best model for adaptive data-driven bundling strategy generation which is presented in the following results section.

# Results

The evaluation results of DT and KNN and ARM as ML methods for bundling recommendation generation are discussed in this section. All three model’s evaluation took place on a preprocessed dataset. The results are judged based on how well it predicts, as well as how it helps with real-world e-commerce problems like better bundle design, more personalized recommendations and improved handling of inventory.

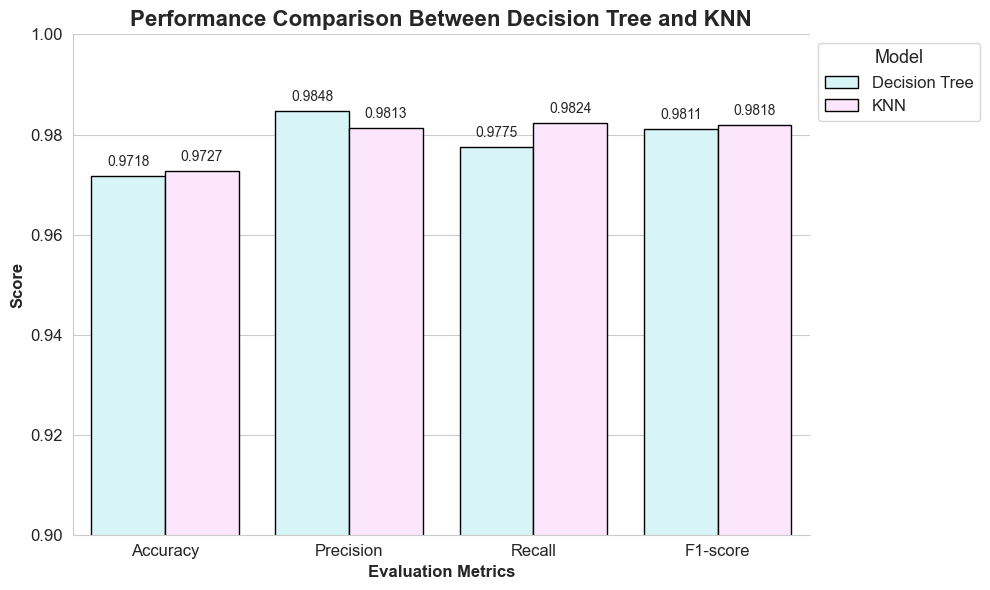
A grid search optimization with 5-fold cross-validation helped achieve the optimal configuration of the DT classifier. The optimal model configuration included 'gini' as the criterion and 20 as the max\_depth value along with min\_samples\_leaf set to 10 and min\_samples\_split set to 30. The trained model demonstrated 97.18% overall accuracy and precision of 0.98 and recall of 0.98 and F1-score of 0.98 for correctly identifying products that would benefit from bundling. Results from the confusion matrix displayed 60,980 cases of true negative predictions and 190,564 cases of true positive predictions as well as minimal classification errors which included 3,627 false positives and 3,420 false negatives. The results prove that DT can choose bundles that match user preferences, so e-commerce platforms can use rules to create bundles that make sense and reflect actual buying behavior.

The employed KNN classifier using Euclidean distance performed similarly to the previous models by attaining 97.27% accuracy during training with scaled features. The classification report demonstrated a precision value of 0.98 and recall value of 0.98 and F1-score of 0.98 for the positive class, which matched the DT results. KNN demonstrates suitability for proximity-based bundle recommendation because its confusion matrix demonstrates strong agreement between actual and predicted labels. KNN demonstrates exceptional value in personalization applications because it uses feature closeness to suggest similar products. KNN is effective at recommending similar products, which is why it is an ideal fit for e-commerce personalized bundling. It encourages users to interact more by suggesting bundles based on user’s personal choices which is now necessary for good recommendations.

Using the FP-Growth algorithm, the ARM technique generated association rules from frequent itemsets obtained from user transaction baskets. The analysis focused on a selected group of the top 50 rules through an evaluation of support, confidence and lift metrics. The strongest product pairings emerged from rules with lift values above 900 and confidence levels exceeding 0.9 such as item 590 ⇒ 1206 and item 5695 ⇒ 5693. The rule (1206 ⇒ 590) demonstrated a lift value of 941.68 and confidence rate of 0.93 which indicates its potential for bundling applications. Large transactional data enables the discovery of purchasing associations that serve as valuable guidance for bundling decision support. This information helps a lot when setting up static or promotional bundles on e-commerce sites, particularly when business want to offer popular combinations that represent real customer purchases in large numbers.

## Comparative Analysis

The three models delivered outstanding prediction quality, the DT generating rules and adaptable usage environments which were easy to interpret along with KNN creating precise recommendation results and ARM supplied superior pattern mining. KNN produced slightly better results than DT through the evaluation metrics where KNN achieved slightly better accuracy, recall and F1-score but DT showed a slight edge in precision. The data indicates that KNN generates better aggregate performance by correctly classifying relevant bundles while maintaining slightly lower levels of precision when compared to DT. Each model is shown to be advantageous for e-commerce. DT helps with easy-to-explain grouping, KNN improves personalized recommendations, and ARM is suitable for finding common pairs of products for bundles. As a result, e-commerce sector can select or mix models that fit their marketing and operations, as illustrated in Figure 2.



**FIGURE 2.** Performance comparison of Decision Tree and KNN

ARM was evaluated based on the strength and quality of the discovered item associations. The generated association rules demonstrate the strength of item-to-item through lift values which increase with stronger associations while confidence measures the likelihood of co-purchases. The size and color of each point represents the support value. The larger and darker points indicate a more frequent occurring itemsets. By using these patterns, e-commerce sector can easily find the most common product combinations customers buy which helps businesses develop useful bundle campaigns. The combination of high lift and confidence in these rules proves that ARM is effective at picking up significant co-purchase behavior in a large set of data, as seen in Figure 3.

A comparative summary of the model’s performances is provided. The analysis highlights both strengths and limitations of each of the ML techniques that were used. Among all the ML techniques used, ARM had the best product associations thanks to its strong lift and support, whereas DT and KNN achieved excellent classification results based on both user behavior and product traits. The abilities of ARM, DT and KNN are useful in business whereas ARM helps find groups of items commonly bought, DT explains the logic for creating bundles and KNN recommends products to each customer individually. This evaluation shows how each technique can be put into practice in the e-commerce sector, depending on the businesses’ aims, as demonstrated in Table 1.

The experimental results establish that ML approaches driven by data can successfully make product bundling recommendations. The evaluation metrics showed high performance results from all the models with ARM uncovered global frequency patterns between items while KNN produced individual-specific recommendations through item similarity modeling and DT delivered a readable set of rules. The experimental outcomes create a solid basis to choose the optimal model selection according to bundling strategies and business requirements.

A graph with a chart and a diagram

AI-generated content may be incorrect.

**FIGURE 3.** Confidence versus lift scatter plot of association rules from ARM (FP-Growth)

**TABLE 1**. Summary of model comparison

|  |  |  |  |
| --- | --- | --- | --- |
| **Technique** | **Accuracy** | **Strengths** | **Limitations** |
| Decision Tree | 97.18% | Interpretable rules; context-based logic | May overfit without pruning |
| K-Nearest Neighbors (KNN) | 97.27% | High accuracy and user-specific predictions | Needs enough user history |
| ARM (FP-Growth) | - | High lift & support and strong associations | Not personalized |

The experimental result of this research establishes that ML techniques driven by data can successfully generate great product bundling recommendations. All three models delivered exceptional performance according to the evaluation metrics. All models delivered different benefits for recommendation purposes where DT generated readable rules and KNN produced item recommendations through similarity models and ARM discovered item-frequency relationships among various consumers. As a result, e-commerce sector can use these outcomes to introduce targeted bundling, choosing either rule-based, user-personalized or pattern-driven methods based on the businesses goals and understanding of customer behavior.

# Discussion

From the evaluation results, machine learning techniques add significant value to product bundling within the e-commerce domain. All three models evaluated in the study, namely DT, KNN, and ARM contributed uniquely in the domain. The high accuracy rates of DT and KNN specifically validate that predictive models effectively identify products appropriate for bundling; meanwhile, ARM identifies strong associations between products based on customer co-purchase behaviors.

The DT model provides a balanced prediction along with interpretability. The transparent rules in output make bundling choices clear for e-commerce sector, enabling businesses to use data for planning and marketing. The model achieves its strength through decision path modeling that uses product attributes and user features to provide logical structures for product bundling strategies. For DT models, methods to prevent overfitting were quite essential when dealing with complex or highly imbalanced datasets.

KNN is excellent in personalization since it recommends items closely based within the feature space. KNN allows the system to formulate a customized package for users exhibiting similar behaviors to others. This is in line with e-commerce platforms, which require personalization to boost the experience and engagement of customers. Proximity-based learning was highly effective with the KNN model due to its remarkable precision and recall values when dealing with large volumes of user interaction data.

The strength of ARM lies in its ability to detect powerful item relationships which enables it to create both static and promotional bundles effectively. ARM uses frequent co-purchase patterns to put together bundles that are based on real shopping habits among many customers. The discovery of association rules with elevated lift and confidence measures through ARM creates a strong data-based structure for bundle development. The inability of ARM to consider individual user behavior reduces its capability for creating personalized bundles relative to DT and KNN methods. Even though the individual experience in ARM is basic, it is very good at spotting popular patterns for mass-market campaigns, catalogs or homepage promotions.

Overall, these findings confirm that different ML techniques can support various bundling strategies, ranging from fixed product combinations to personalized offerings. Conducting a comparative evaluation provides valuable insights into which techniques best meet specific operational goals in e-commerce. The study highlights that data-driven bundling approaches not only improve operational efficiency but also better adapt to evolving customer purchasing behaviors, offering a strong alternative to traditional rule-based bundling methods.

Overall, the research demonstrates that multiple ML techniques enable business to create bundling approaches which range from standard product packages to individualized bundles. A comparative analysis allows e-commerce sector to decide on the best bundling approach for their business, customers and data. The study demonstrates that data-driven bundling approaches not only improve business operations but also better adapt to the evolving of customer purchasing behaviors which offers a strong alternative to traditional rule-based bundling methods.

# Conclusion

This research studied and evaluated a ML based product bundling recommendation system designed for e-commerce platforms. The system employed three approaches which are DT, KNN, and ARM to generate product bundle recommendations with practical value. The DT model reached high interpretability through its rule-based rules while the KNN provided bundles that matched user preferences through item similarity. The high-lift association rules in ARM extracted powerful product relationships from historical transaction data. Every ML technique played a unique role in overcoming an issue in e-commerce bundling, DT for business logic, KNN for individual user targeting and ARM for large-scale pattern detection.

Comparative analysis showed that all three ML techniques produced high results and brought unique strengths suitable for different system requirements. Rule generation through the DT suits context-sensitive bundling aligned with business decision-making, while KNN works great for recommending personalized items to improve customer experience. ARM can uncover items that are commonly purchased together which benefits both static and promotional bundling campaigns. Thanks to these insights, e-commerce platforms can find new ways to manage product packaging and please its customers.

Future research needs to create a single hybrid recommendation solution which dynamically merges rule-based and similarity-based and classification-based recommendation methods. Additionally, product bundling in e-commerce sector would gain an enhanced adaptability and effectiveness by incorporating a real-time user data, contextual factors, and reinforcement learning.

# References

1. “Amazon Electronics Products Sales,” (n.d.). https://www.kaggle.com/datasets/edusanketdk/electronics
2. W.-E. Kong, T.-E. Tai, P. Naveen, and H.A. Santoso, “Performance Evaluation on E-Commerce Recommender System based on KNN, SVD, CoClustering and Ensemble Approaches,” Journal of Informatics and Web Engineering  **3**(3), 63–76 (2024).
3. E. Robbi, M. Bronzini, P. Viappiani, and A. Passerini, “Personalized bundle recommendation using preference elicitation and the Choquet integral,” Front. Artif. Intell. **7**, 1346684 (2024).
4. I.H. Sarker, “Machine Learning: Algorithms, Real-World Applications and Research Directions,” SN COMPUT. SCI. **2**(3), 160 (2021).
5. R. Somya, E. Winarko, and S. Priyanta, “A hybrid recommender system based on customer behavior and transaction data using generalized sequential pattern algorithm,” Bulletin EEI **11**(6), 3422–3432 (2022).
6. J.M. Spreitzenbarth, C. Bode, and H. Stuckenschmidt, “Designing an AI purchasing requisition bundling generator,” Computers in Industry **155**, 104043 (2024).
7. H. Tzaban, I. Guy, A. Greenstein-Messica, A. Dagan, L. Rokach, and B. Shapira, “Product Bundle Identification using Semi-Supervised Learning,” in *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, (ACM, Virtual Event China, 2020), pp. 791–800.
8. H. Wang, “Consumer Behavior Analysis and Enterprise Marketing Strategy Optimization Based on Decision Tree Model and Association Rule Algorithm,” IJCAI **49**(7), (2025).
9. A. Al-Khulaqi, N. Palanichamy, S.C. Haw, and S.C. Raja, “Evaluating Machine Learning and Deep Learning Algorithms for Predictive Maintenance of Hydraulic Systems,” Int. J. Adv. Sci. Eng. Inf. Technol. **15**(1), 52–59 (2025).
10. J.S.A. Tan, Z. Che Embi, and N. Hashim, “Comparison of Machine Learning Methods for Calories Burn Prediction,” Journal of Informatics and Web Engineering **3**(1), 182–191 (2024).doi: 10.33093/jiwe.2024.3.1.12
11. S. Xu, H. Ma, Y. Ma, X. Liu, L. Meng, X. Meng, and T.-S. Chua, “Headache to Overstock? Promoting Long-tail Items through Debiased Product Bundling,” arXiv:2411.19107 (2024).
12. Y. Ma, X. Liu, Y. Wei, Z. Tao, X. Wang, and T.-S. Chua, “Leveraging Multimodal Features and Item-level User Feedback for Bundle Construction,” in *Proceedings of the 17th ACM International Conference on Web Search and Data Mining*, (ACM, Merida Mexico, 2024), pp. 510–519.
13. F.T. Abdul Hussien, A.M.S. Rahma, and H.B. Abdul Wahab, “Recommendation Systems For E-commerce Systems An Overview,” J. Phys.: Conf. Ser. **1897**(1), 012024 (2021).
14. R. Oetama, “Product Bundling Strategy for Office Supplies Retailer through Association Rules Mining: Comparative Study of Apriori and ECLAT Algorithms,” Ijcs **12**(6), (2024).
15. C C.-H. Weng, and C.-K. Huang, “A new bundling model to promote the worst selling products with deep learning approaches,” International Journal of Market Research **67**(4), 423–444 (2025).
16. Ahmad Syaeful Ma’arief, Rudi Kurniawan, and Saeful Anwar, “Improvement of Fashion Product Sales Association Model in the Largest Store on Melgit Official Lazada with the Frequent Pattern Growth Algorithm,” Journal of Artificial Intelligence and Engineering Applications **4**(2), 1557–1461 (2025).
17. Z.-T. Yap, S.-C. Haw, and N.E. Binti Ruslan, “Hybrid-based food recommender system utilizing KNN and SVD approaches,” Cogent Engineering **11**(1), 2436125 (2024).
18. S.E. Putra, and M. Ilmi, “Application of K-Nearest Neighbor Algorithm for Consumer Behaviour Identification and Product Personalisation Based on Big Data Analysis,” JurnalEcotipe **11**(2), 205–213 (2024).
19. J.-P. Cheng, and S.-C. Haw, “Mental Health Problems Prediction Using Machine Learning Techniques,” International Journal on Robotics, Automation and Sciences **5**(2), 59–72 (2023). doi: 10.33093/ijoras.2023.5.2.7
20. S.A. Lashari, M.M. Khan, A. Khan, S. Salahuddin, and M.N. Ata, “Comparative Evaluation of Machine Learning Models for Mobile Phone Price Prediction: Assessing Accuracy, Robustness, and Generalization Performance,” Journal of Informatics and Web Engineering **3**(3), 147–163 (2024). doi: 10.33093/jiwe.2024.3.3.9
21. W.-W. Lee, N. Hashim, and S. Al-Juboori, "User behaviour prediction in e-commerce using logistic regression," Journal of Informatics and Web Engineering 4(3), 299–323 (2025). https://doi.org/10.33093/jiwe.2025.4.3.18