Machine Learning for Recommending Consumer Electronics

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Abstract **–This research examined the influence of Machine Learning on consumer electronics recommendations through a mobile application in Trujillo. A system based on the Random Forest algorithm was developed to suggest categories and display products according to predictions. Three indicators were analysed: number of recommendations, recommendation effectiveness, and average search time. Using a true experimental design with 190 records per group, the Mann–Whitney test ($p = 0.001$) revealed statistically significant differences. The results show that the use of Machine Learning improved the user experience by increasing the number of recommendations, enhancing their perceived usefulness, and reducing search time. These findings highlight the practical value of machine learning–based recommender systems for e-commerce platforms, as they can support more efficient product discovery and improve decision-making processes for both users and online retailers.**

Keywords **– Machine learning, e-commerce, electronics, mobile, Random Forest.**

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1. Introduction

This section presents the background and justification for the study, highlighting the current limitations of recommendation systems in the context of consumer electronics e-commerce. It discusses regional and global challenges, including personalization, data scarcity, privacy concerns, and the need for more advanced approaches such as machine learning and natural language processing to enhance user experience and recommendation effectiveness.

Despite the rapid growth of e-commerce in recent years, consumer electronics websites in the city of Trujillo still offer poorly personalized recommendations due to the limited use of data and predictive models, which negatively affects the customer experience. E-commerce encompasses business and commercial activities driven by information technologies, particularly those based on networked systems; however, its implementation in the local market still faces several challenges [1].

This highlights the importance of incorporating advanced techniques such as Machine Learning to improve recommendation accuracy and enhance user experience. A study conducted in Vietnam indicated that, although large volumes of data and various mainstream methods exist to anticipate consumer preferences, many recommendation systems remain too basic. This is partly due to the omission of key variables such as seasonality, inventory availability, or promotional campaigns. In addition, one of the most significant challenges continues to be the cold-start problem, which hampers the generation of effective recommendations for new users or products [2].

Research in China revealed that the rapid growth of e-commerce, with an estimated annual increase of 40%, has led to an information overload that complicates efficient product searches for users. In this context, recommendation systems have emerged as key tools to deliver personalized information and improve the shopping experience. However, many of these systems still fail to cater precisely to individual preferences, which negatively impacts both customer satisfaction and commercial competitiveness [3].

Another study conducted in the East Asian region pointed out that current approaches are beginning to show limitations when dealing with large-scale, high-dimensional data. This situation has driven the need to explore more effective solutions capable of extracting relevant patterns and predicting user interests more accurately, thus improving the overall experience [4].

Studies carried out in Europe have also revealed difficulties similar to those identified in other regions regarding the performance of recommendation systems [2]. Among the main limitations are data scarcity during the initial interaction with new users, scalability issues when handling large volumes of information, the lack of contextual integration in recommendations, and difficulties in adapting to consumers' changing preferences [5].

A study conducted in London highlighted that user privacy restrictions represent a significant obstacle to the development of effective recommendation systems, particularly in cold-start contexts where new users have not yet generated sufficient data. It was found that some systems overlook fundamental psychological dimensions, such as emotions or intuition, which limits a comprehensive understanding of consumer behavior. A survey revealed that many current algorithms continue to rely on superficial behavioral patterns without incorporating users' psychological factors, which hinders the achievement of an adequate level of personalization [6].

On the other hand, recent research noted that the combination of machine learning techniques with natural language processing (NLP) is becoming increasingly common in the design of recommendation systems. These systems typically incorporate different approaches, among which content-based filtering, collaborative filtering, and hybrid models stand out [7].

2. Objectives

This section outlines the general and specific objectives of the study, which guide the development and evaluation of a machine learning–based recommendation system aimed at improving the user experience in the context of consumer electronics e-commerce in Trujillo.

The general objective of this research is to recommend consumer electronics products from websites in Trujillo using Machine Learning during the first semester of 2025. In addition, the following specific objectives were established: 1) To increase the number of consumer electronics product recommendations on websites in Trujillo, 2) To improve the recommendation effectiveness of consumer electronics websites in Trujillo, and 3) To reduce the average search time for consumer electronics products for users of websites in Trujillo.

3. Methodology

This section describes the methodology used in the study, including the type of research, the methodological design, and the procedures followed to evaluate the proposed machine learning–based recommendation system.

3.1. Type and Research Design

This is an applied research study in which a machine learning model was designed and implemented through a mobile application to recommend consumer electronics products from websites to users in Trujillo. The approach is oriented toward solving practical problems, aiming not only to generate knowledge but also to apply it in offering concrete and functional solutions [8]. The study followed a quantitative approach, supported by the analysis of three indicators: number of recommendations (NR), recommendation effectiveness (RE), and average search time (AST). The results are presented in tables, accompanied by a descriptive analysis of each evaluated indicator.

These indicators make it possible to objectively assess the performance of the recommendation system by detecting patterns and trends in the data. The tables help interpret the numerical values obtained and examine their variability. This quantitative approach, backed by statistical tools, not only facilitates outcome prediction but also enables the verification of relationships among variables and the generalization of findings [9]. All of this is aimed at improving the three key indicators of this study, number of recommendations, the effectiveness of the recommendations, and the average search time for products.

The research adopted a true experimental design, in which a specific group was established to observe results under controlled conditions. According to the Frascati Manual, experimental development involves applying existing knowledge to create new products or improve existing ones [10]. In this study, the experimental group consisted of data collected from users who directly interacted with the mobile application that implements the model. In parallel, a control group was formed with carefully selected and monitored data to ensure information quality, minimize potential biases, and enable a more accurate assessment.

This research is inherently quantitative in nature, focusing on the collection of measurable data and supported by a robust methodology to evaluate and compare the performance of the recommendation system. It also facilitates the identification of potential areas for improvement [11].

3.2. Variables and Operationalization

This section describes the variables considered in the study and explains how they were operationalized for analysis. Each variable is clearly defined by specifying its role within the research model, the type of measurement applied, and the criteria used to transform conceptual constructs into measurable indicators. This operationalization ensures consistency, replicability, and alignment between the research objectives, the data collected, and the analytical methods employed.

Independent Variable: Machine Learning integrates multiple analysis strategies designed to create algorithms that extract information from data for the purpose of explanation, classification, or prediction [12].

Dependent Variable: Recommendations of consumer electronics products are the result of a personalized process that, in the context of e-commerce, reduces the user's search effort by presenting products with high estimated utility that is, products the user is likely to find relevant or desirable [13].

Population: For this study, the target population was defined as users of e-commerce platforms interested in consumer electronics products.

Sample and Sampling: Based on this population, the study worked with a sample of 385 simulated records of potential customers between 18 and 35 years old. Researchers selected convenience sampling due to its inherent benefits [14].

3.3. Material and Methods

This subsection presents the adapted approach, the instruments used for data collection, and the procedure for implementing the machine learning model. Finally, it describes the technical strategies applied during the construction of the recommendation system, considering the data sources and development environment used.

Techniques and Instruments: Information gathering was made via indirect observation. This technique is a key resource in scientific research, allowing for the orderly and structured recording of observable phenomena without directly intervening in them [15].

In addition, structured observation forms were employed to collect data for each indicator.

3.4. Development Through Mobile -D

The Mobile-D (MD) methodology was used as it is an effective project management framework that emphasizes test-driven development, continuous integration, and optimization, enhancing software development processes [16].

3.4.1. Exploration

The Flutter framework was used for mobile application development. Flutter is an open-source software development kit (SDK) developed by Google that allows building cross-platform mobile applications from a single codebase; it was officially released in 2018 [17].

During this phase, Flutter's features were evaluated, prioritizing aspects such as performance, cross-platform compatibility, ease of integration with external APIs, and development speed. Flutter was selected for its widget-based architecture, its own graphics engine (Skia), and the ability to maintain a smooth interface across different devices an essential feature for applications that consume machine learning models remotely.

Additionally, design patterns for interface and mobile usability tailored to product recommendation applications were reviewed. These included navigation structures, modularity, and consumption of RESTful services, which would be fundamental for integrating the externally hosted machine learning model.

3.4.2. Initialization

Initial Settings configuration, the preliminary design, and required resources were defined. A layered architecture was established (presentation, domain, infrastructure, and configuration). Endpoints were set up to consume the machine learning model via HTTP, and essential libraries such as http, provider, and flutter_dotenv were integrated. Additionally, the first interfaces were designed and later refined during development, as illustrated in Figure 1.

Figure 1. Initial view prototype

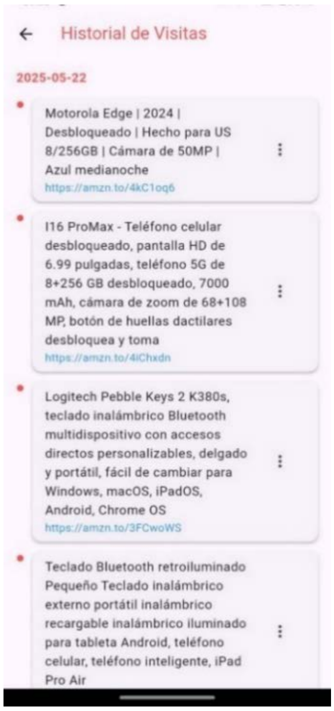

Figure 3. Visit record view

3.4.3. Production

In this phase, the functional development of the mobile application was consolidated by integrating the modules built in previous stages. Key functionalities were implemented, including consumption of the machine learning model through a REST API, visualization of recommended categories, browsing history, ratings, and comments. Furthermore, navigation flows were validated to ensure smooth interaction between the user interface, business logic, and external services, as illustrated in Figure 2, Figure 3, and Figure 4.

Figure 2. Homescreen

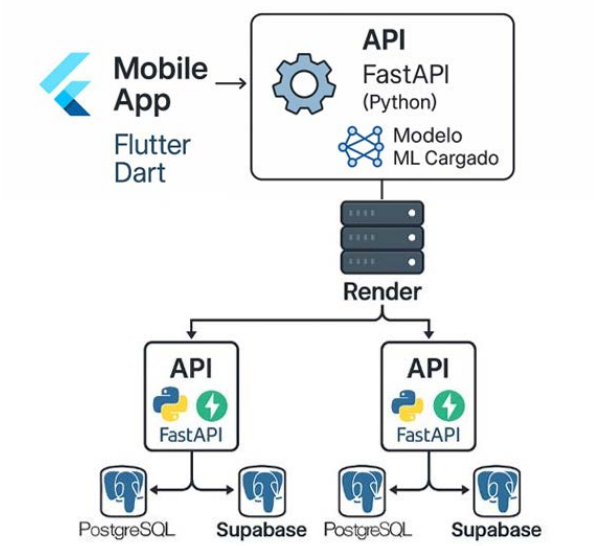

Figure 4. Software architecture

3.4.4. Software Stabilization and Testing

During this phase, functional and performance tests were conducted to ensure the stability of the mobile application. Detected bugs were fixed, internal processes were optimized, and the consistent behavior of the implemented functionalities was verified. Additionally, visual elements were adjusted, and a smooth user experience was ensured prior to final validation.

3.5. Data Analysis Methodology

To assess project results, specific hypotheses were formulated for each indicator of the dependent variable. For the number of recommendations of consumer electronics products (NR), the alternative hypothesis (Ha) posits that the use of Machine Learning increases the NR in the experimental group (NR–EG) compared to the control group (NR–CG). In the case of the effectiveness of recommendations of consumer electronics products (RE), Ha proposes that Machine Learning improves the RE in the experimental group (RE–EG) versus the control group (RE–CG). Lastly, for the average search time of consumer electronics products (AST), Ha states that Machine Learning reduces the AST in the experimental group (AST–EG) compared to the control group (AST–CG).

Descriptive analysis: For the indicators Number of Recommendations (NR), Recommendation Effectiveness (RE), and Average Search Time (AST), the data were characterized by calculating the average for both the control group (CG) and the experimental group (EG). Additionally, a reference value was established based on prior studies and complemented by empirical analysis from an expert in the field of e-commerce. The dataset was then tallied, and an overall average was calculated. In both groups, the number of values exceeding the group average and the reference value was counted, and the corresponding percentage was determined. Finally, a descriptive table was created showing the mean and median, using Jamovi software.

Inferential analysis: A normality test was applied to the data collected from the control group and the experimental group. Since the number of records exceeded 50, the Kolmogorov–Smirnov test was used. The results indicated that none of the datasets evaluated for each indicator followed a normal distribution. Therefore, the non-parametric Mann–Whitney test was applied to determine whether the independent variable caused significant differences in the results.

4. Findings

This section presents the results derived from the collected data, focusing on two main areas. The first involves the descriptive analysis of the indicators, conducted using Jamovi software. The second area corresponds to the inferential analysis, which includes both normality testing and hypothesis testing for each indicator.

4.1. Descriptive Analysis

The trained machine learning model demonstrates excellent performance, enabling it to recommend consumer electronics products aligned with users' current interests during browsing. This predictive model not only improves the quality of the suggestions but also adapts dynamically to changes in user preferences, adjusting recommendations based on recent behavior and browsing history. A descriptive analysis was applied to the three evaluated indicators: number of recommendations (NR), recommendation effectiveness (RE), and average search time (AST). The objective was to directly compare the values observed in the experimental group (EG) and the control group (CG), allowing for a practical and detailed evaluation of the recommendation system's performance.

As shown in Table 1, 41.05% of the number of recommendations of consumer electronics products (NR) were above their average value (103). Additionally, 100% of the NR values in the proposal for the experimental group (EG) exceeded the target value (10). Finally, it was determined that 100% of the NR values in the proposal for the experimental group (EG) were greater than the average (9) observed in the proposal for the control group (CG).

Table 1. Recommendations number descriptive analysis

	CG test		EG test	
Average	9		103	
Goal			10	
No higher than average		78	190	190
% Higher than average		41.05	100	100

As shown in Table 2, 43.16% of the recommendation effectiveness of consumer electronics products (RE) exceeded their average value (82). Additionally, 2.04% of the RE values in the proposal for the experimental group (EG) surpassed the target value (12). Finally, it was determined that 17.89% of the RE values in the proposal for the experimental group (EG) were greater than the average (10) observed in the proposal for the control group (CG).

Table 2. Recommendation effectiveness descriptive analysis

Average	CG test		EG test	
Goal	10		8	
Average			12	
Goal		82	17	34
No higher than average		43.16	2.04	17.89

As shown in Table 3, 95.26% of the average search time of consumer electronics products (AST) exceeded their average value (1). Additionally, 100% of the AST values in the proposal for the experimental group (EG) surpassed the target value (4). Finally, it was determined that 100% of the AST values in the proposal for the experimental group (EG) were greater than the average (4) observed in the proposal for the control group (CG).

Table 3. Average search time descriptive analysis

	CG test		EG test	
Average	9		1	
Goal			2	
No Higher than average		181	190	190
% Higher than average		95.26	100	100

4.2. Inferential Analysis

According to the data presented in Table 4, for all three evaluated indicators number of recommendations of consumer electronics products (NR), recommendation effectiveness of consumer electronics products (RE), and average search time of consumer electronics products (AST) the sample size for both the control group (CG) and the experimental group (EG) exceeded 50 cases. Therefore, the Kolmogorov–Smirnov test was applied to verify the normality of the data. For NR, the results showed that in the CG, the p-value was 0.001, indicating a non-normal distribution, as it is below the significance threshold of 0.05. In contrast, the EG reported a p-value of 0.055, which indicates a normal distribution. Regarding RE, both the CG and the EG had p-values below 0.05, confirming non-normal distribution in both groups. Similarly, for AST, both groups also presented p-values below 0.05, once again confirming a non-normal distribution. Although one group (EG) showed a normal distribution for NR, the rest of the results reflect non-normality across indicators.

Table 4. Kolmogorov-Smirnov normality test

	statistic	P
NR (CG)	0.2670	0.001
NR (EG)	0.0972	0.055
RE (CG)	0.3167	0.001
RE (EG)	0.1626	0.055
AST (CG)	0.2394	0.001
AST (EG)	0.3476	0.001

Therefore, in accordance with the established methodological criteria, the non-parametric Mann–Whitney U test was applied for the inferential analysis of the three indicators, given that the samples were independent and non-normal distributions were observed in at least one of the groups.

The results of this statistical test showed a p-value of 0.001 for each of the indicators, which is lower than the established significance level (α = 0.05). This provides sufficient evidence to reject the null hypotheses and accept the alternative hypotheses. Accordingly, for the first indicator (number of recommendations of consumer electronics products), the null hypothesis which held that there was no significant difference between the groups is rejected, and the alternative hypothesis is accepted, indicating that the use of Machine Learning positively influences the increase in recommendations. For the second indicator (recommendation effectiveness of consumer electronics products), the null hypothesis is also rejected and the alternative hypothesis accepted, demonstrating that Machine Learning significantly improves recommendation effectiveness. Finally, for the third indicator (average search time of consumer electronics products), the null hypothesis is again rejected and the alternative hypothesis accepted, leading to the conclusion that Machine Learning significantly reduces the average product search time. These results confirm that the implementation of the machine learning–based system has a positive and statistically significant impact on all analysed indicators.

5. Discussion

This section analyses the results in relation to previous studies, highlighting the effectiveness and limitations of the proposed machine learning–based recommendation system. It also examines the broader implications of the findings and possible strategies for future improvement.

The findings of this research demonstrate that the recommendation effectiveness (RE) generated by the system is closely tied to both the accuracy of the model and the quality of the input data. These results align with those reported in a study conducted in Lisbon, where various recommendation algorithms such as ItemKNN, SVD, and NCF were evaluated. That analysis concluded that both accuracy and diversity are fundamental factors in enhancing user satisfaction on e-commerce platforms. Their results showed that traditional methods achieved a precision of 0.5146 and a satisfaction level of 0.4820, highlighting the limited impact of relying solely on accuracy. In contrast, deep learning–based systems demonstrated improvements in both precision and diversity, resulting in better overall user experience. [18].

This supports the idea that although the model proposed in this research (based on Random Forest) achieved a precision of 89.59%, its ability to address diverse user needs could be further enhanced through the design of complementary strategies.

Some challenges identified in this study such as lower accuracy in certain categories or the effect of outlier user behavior are consistent with findings reported in a study conducted in Berlin [19]. That study emphasized that while recommendation systems are essential tools for managing digital information overload, they still face technical challenges such as the cold-start problem, data bias, and accuracy limitations. Their proposal included strategies like randomization to improve overall system performance.

Additionally, a study carried out in India also emphasized the importance of filtering biased information in high-volume e-commerce environments. This challenge was similarly observed in the present study during the training phase, particularly with underrepresented categories. Their use of frequent itemset mining algorithms improved both the effectiveness and accuracy of recommendations by relying on real user preferences, allowing the system to adapt in real time [20].

Although this study applies a different logic through the Random Forest model it presents functional similarities, as it responds dynamically to user input without requiring real-time model updates. This has proven to be an effective approach for adapting to evolving user interests. These findings underscore the importance of optimizing both content and context from the training phase to enhance the system's utility.

The resulting values are consistent with recent research on personalized recommendation systems in e-commerce environments. A study in Spain found that the use of personalized Top-N recommendation systems significantly reduced users' search time and improved their interaction with suggested products [21]. These findings are in line with the results of the present study, which demonstrated that the use of Machine Learning not only increased recommendation precision but also improved user behavior during the search process. This approach contributes to more efficient decision-making and reduces the cognitive load caused by the overabundance of available options.

6. Conclusion

This section presents the main conclusions derived from the study, emphasizing the impact of the Random Forest algorithm on the improvement of recommendations in consumer electronics e-commerce. It also outlines key suggestions for future research and system optimization.

It is concluded that when using Machine Learning specifically the Random Forest classification algorithm the number of recommendations of consumer electronics products increases.

This demonstrates that the developed model has a strong ability to generate recommendations that align with user interests.

When Machine Learning is applied specifically the Random Forest classification algorithm the recommendation effectiveness also improves. These results indicate that the precision achieved during training was sufficient to enhance the relevance and usefulness of the recommendations provided.

Moreover, the application of Machine Learning again using the Random Forest classification algorithm reduces the average search time. These findings demonstrate that the implemented system facilitated navigation, shortened the exploration process, and supported quicker decision-making.

The results confirm that the methodology applied in this study a true experimental design and the implementation of a classification model based on the Random Forest algorithm, using data collected through Amazon's affiliate program enabled an effective analysis of the influence of Machine Learning on product recommendations. However, it is suggested to further optimize the dataset and apply new strategies to address the limitations observed during training, as well as to explore more advanced models to improve precision in underrepresented categories.

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