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Integrated Recommendation System in ChatGPT to Analyze Post-purchase Behavior of E-commerce Store Users

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Abstract— *Recommender systems have had a great development in recent years, helping exponentially in the e-commerce sector. This has many applications to improve user behavioral factors with different filtering techniques; however, most of these systems lack a presentation and interaction model that really influences users. In this context, e-commerce sites are looking for different strategies to allocate the recommendations seen by the online user in an accurate and timely manner; still, reviewing different articles it is not very clear whether the way in which the recommended items are presented has a positive impact on user behavior. On the other hand, conversational artificial intelligence systems technology had a large size, highlighting ChatGPT as an innovative tool. Finally, this research aims to validate whether the implementation of an integrated SR in ChatGPT influences the post-purchase behavior of users in an e-commerce store. The results show that by leveraging the potential of conversational AI to deliver more effective and personalized recommendations, there is a 34.15% increase with respect to user recommendation, while in the purchase of recommended products there is an exponential increase of 54.05%; Likewise, it is evident that users who make repurchases after 14 days from their initial purchase have an increase of 46.67%; finally, that the repurchase of products from the e-commerce store has a slight significant increase of 9.52%.*

Keywords-Recommendation System, ChatGPT. Post-purchase, E-commerce, Personalization

Sistema de Recomendación Integrado en ChatGPT para Analizar el Comportamiento Post-compra de Usuarios de una Tienda E-commerce

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Abstract*— Recommender systems have had a great development in recent years, helping exponentially in the electronic commerce sector. This has many applications to improve user behavior factors with different filtering techniques; however, most of these systems lack a presentation and interaction model that really influences users. In this context, e-commerce sites seek different strategies to allocate recommendations viewed by the online user in an accurate and timely manner; even so, reviewing different articles it is not very clear if the way in which recommended articles are presented has a positive impact on user behavior. On the other hand, the technology of conversational artificial intelligence systems had a great size, highlighting ChatGPT as an innovative tool. Finally, this research seeks to validate whether the implementation of an integrated SR in ChatGPT influences the post-purchase behavior of users of an e-commerce store. The results show that by taking advantage of the potential of conversational AI to provide more effective and personalized recommendations, there is an increase of 34.15% with respect to the recommendation of users, while in the purchase of recommended products there is an exponential increase of 54.05%; Likewise, it is evident that users who make repurchases after 14 days from their initial purchase have an increase of 46.67%; finally, that the repurchase of products from the e-commerce store has a slight significant increase of 9.52%.
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I. INTRODUCTION

Today, in the context of the digital age, e-commerce has experienced significant growth, allowing users with the convenience of browsing and buying a broad array of products from the comfort of their residences. This increase has been largely driven by the impact of COVID-19, a global crisis that has led to a greater preference for online purchases over physical store purchases, as highlighted by reports from the United Nations (UN) [1]. However, in this highly competitive environment, one of the main concerns facing online stores lies in their ability to retain existing customers and encourage repeat purchases [2]. Customer loyalty has become a critical factor for the success and sustainable growth of online stores in this digital landscape.

In this context, recommender systems (RS) play a crucial role by providing personalized suggestions to users, based on their preferences and previous buying behaviors like in Fig. 1. These systems have been shown to be highly effective in enhancing the user experience and significantly increasing the probability of making additional purchases. In fact, various investigations, including the "Recommender Systems Handbook" by Ricci et al. [3], have highlighted the relevance of recommender systems (RS) in the environment of electronic commerce. However, despite its benefits, significant limitations have been identified in traditional recommender systems. These limitations lie in its ability to take full advantage of changing behavioral data and user preferences. As reports by OpenMind [6] and Unite [5] have pointed out, post-purchase behavior data analysis is essential to improve the accuracy and relevance of recommendations. However, these systems face challenges in adapting to constantly changing customer behavior and providing timely and personalized recommendations in real time. This lack of adaptability can result in static and generic suggestions, which fail to effectively meet the particular needs of each user, thus diminishing their effectiveness in driving loyalty and repeat purchases.

To address this critical challenge, an innovative and user behavior-oriented perspective is required. It is proposed to develop a new recommender system (see fig. 1) that combines advanced data analysis approaches and machine learning techniques to overcome the limitations of traditional systems. This new recommendation system will focus on dynamically adapting to changing customer preferences and purchasing patterns, enabling highly personalized and relevant recommendations to be delivered in real time. By integrating post-purchase behavioral data analysis and continuous tracking of customer preferences, this innovative approach aims to provide a highly personalized online shopping experience, increase customer satisfaction, and encourage greater loyalty and repeat purchases in the e-commerce environment.

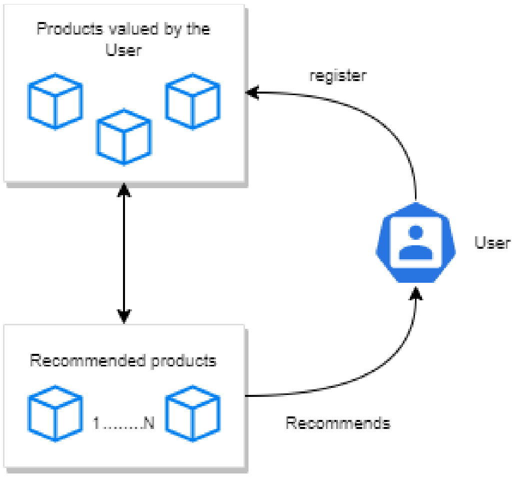

Fig. 1. Basic recommendation system diagram

II. Literature Review

Over time, recommender systems (RS) have experienced remarkable progress in multiple domains, facing the challenge of information saturation on the Internet [7]. Although RSs have managed to mitigate this problem, personalization and evaluation of the quality of recommendations are aspects that require further attention [7][8].

Knijnenburg et al. [8] pointed out in their article that the evaluation of RSs has traditionally focused on analyzing how recommendation algorithms work in relation to the recommendations issued. However, the metrics used, such as precision, recall, f-measure, and MAE, provide a partial view of RS performance since they do not address subjective aspects and user experience [8][9]. It is essential to understand the post-purchase behavior of users in the field of electronic commerce, as this contributes to better understand their preferences and needs [10].

To overcome the limitations of solely system-focused evaluation, approaches have emerged that focus on evaluating how RSs help throughout the purchase flow, including the last step, which is post-purchase [10]. These approaches consider the incorporation of explanations in the presentation of recommendations [10]. These explanations can take various forms, such as text, graphics, or contextual, and allow the user to understand why certain recommendations are offered, building confidence in them [11][9][10].

In the specific context of RSs sensitive to post-purchase behavior in e-commerce stores, the use of explanations for the purpose of increasing user understanding and confidence in recommendations has been investigated [10]. In addition, the need to compare the impact of different forms of exposure on these systems has been observed [10].

On the other hand, RSs based on collaborative filtering often face challenges due to low user-item interactions and cold start issues [12]. To address these problems, techniques that use auxiliary information, such as knowledge graphs, Various approaches have been suggested to enhance the performance of RSs [12]. However, until now, current approaches have not fully exploited the semantic associations present in knowledge graphs [12].

In summary, to evaluate the integration of content-based RS in an artificial intelligence assistant through an e-commerce store, it is necessary to approach the evaluation from a broader perspective, considering subjective aspects and user experience [8][9]. Incorporating explanations into recommendations has been shown to improve user understanding and confidence [11][9][10]. Furthermore, a more thorough comparison of different forms of explanation is required in the specific context of RSs sensitive to post-purchase behavior [10].

III. Methodology

A. Conceptual Design

To begin with the development of technological innovation, a general design of the main components between the interaction and processing between the user and the new recommendation API is carried out. Fig. 2 it is divided into three main sections to create the right environment. First, the UI (User Interface) Chatbot section looks for the query input and output representation dedicated to the user. Second, the recommendation API section integrates the two technologies (ChatGPT and RS) in the same API. Third, the Processing section defines the main functions of each technology integrated into the API.

B. Dialogflow

For the data flow, ChatGPT is used through the API offered by OpenAPI. First configuring the role that the bot will take, the 3.5 architecture and the token required by the API.

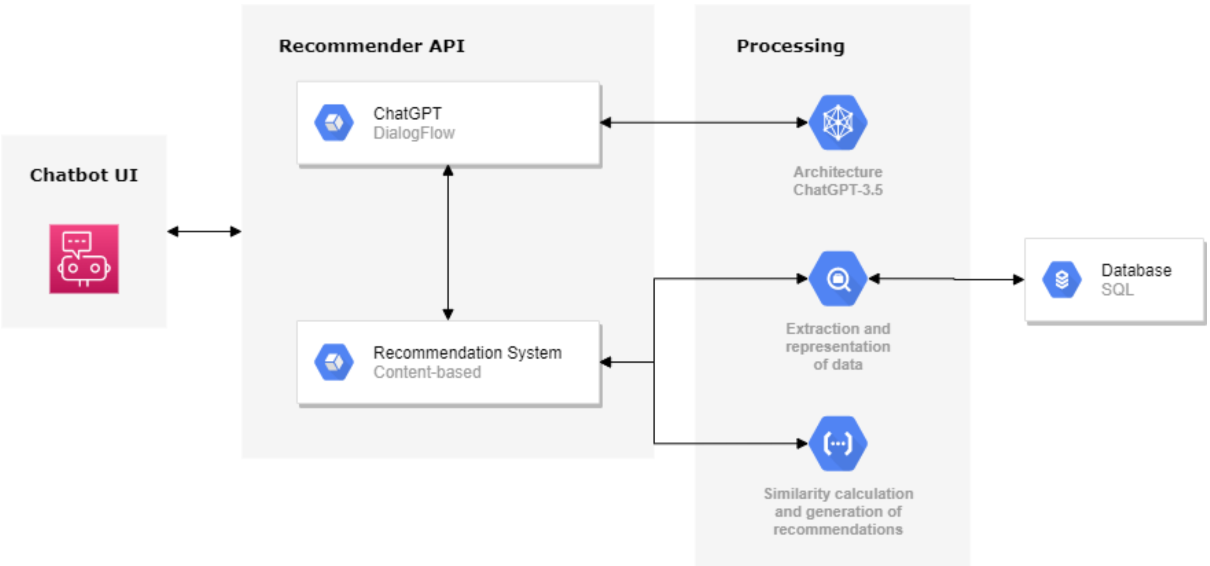

Fig. 2. General Design of the Recommendation API

The main method of the flow dialog oversees identifying if a query is of the recommendation type or not. If ChatGPT detects that it is a recommendation type query, then it generates a special key. When detecting the special key in the response output, the recommended products for the user are obtained. If the user does not have data registered to obtain their preferences, then it will mean that the user is new or has no repurchases, so the flow oversees recommending the popular products of the e-commerce store and thus reformulating the query and response with ChatGPT. The invention of the indicator key is also to avoid overloading the recommender system with a large volume of database requests. In this way, the recommendation system will only generate recommendations when detected by the AI, reducing the load and ensuring a timely response. Also, Fig. 3 highlights in detail the strategic solution regarding the cold start problem that is often mentioned in logic. This problem is a common challenge in RS, especially when there is not enough data to understand the tastes of users, and even more so in content-based systems. This scenario when sufficient data is not accessible to generate personalized recommendationss. What Fig. 3 initially shows is that if a user is new and has not logged into the e-commerce store, a recommendation strategy based on popularity can be applied. In this approach, the most popular products in the store will be displayed to the user. This ensures that new users will have attractive options right from the start and will be able to explore the hottest products on the platform. On the other hand, if a user is logged in but has not made more than one purchase of an item, the popularity strategy can also be used. In this way, the general preferences of the users are taken advantage of to offer attractive options to the user with a limited purchase history.

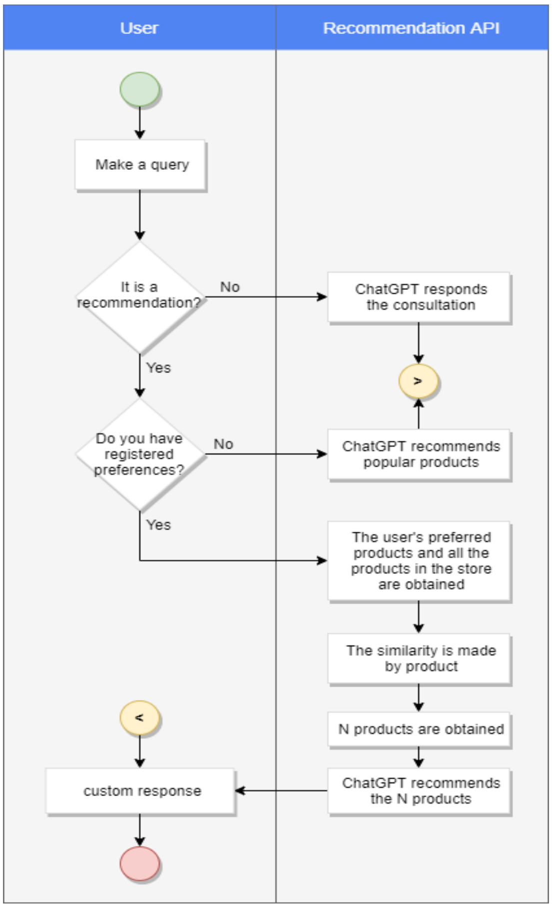

Fig. 3. Flowchart between user and recommendation API

C. Extraction and Representation

For data extraction and representation, a link to the database is made. To begin with, there must be a parameter which is identified by the user, which variable can take the value of zero (if there is no user) or the value of a real identifier of a user registered in the database. Now, if it takes the value zero, it will mean that you are a new user and no product will be recommended based on your preference: in the same way, if the size of your preferences is equal to zero (meaning that you have no registered preferences); Also, this rule is defined in Fig. 3 of the main query flow. Once it is verified that there are registered preferences, then we proceed to call a function called obtain recommendations, which sends the three parameters that are the user identifier, the preferences vector (this vector will store details such as the products purchased by the user and their valuation) and the articles vector (all the articles of the e-commerce store obtained in order to be calculated by similarity).

The first lines of the get recommendations function define the weighted dictionaries and similarities that will be used to calculate the similarity between products. Then, the preferences are iterated but only the preferences of the user who makes the query will be considered. When obtaining the preference, a tour of all the products is carried out and a conditional is carried out in order to make a similarity between the preferred product and the other products and for this with the variable sim (similarity) it is intended to calculate said similarity through the calculate similarity function in which the preferred product and another product from the e - commerce store are sent. After calculating the similarity, the savings and similarities of each product are accumulated. With the ranking's tuple, the normalized score and the product identifier are obtained; Likewise, they are ordered from highest to lowest with the short() method, ensuring that the products with the highest score appeared first in the list. Finally, a last round of products is carried out to obtain the names of the products that are in the ranking, prioritizing only the first three (N = 3 has been defined as a parameter).

D. Similarity Calculation

Through the calculate similarity function in Fig. 4, the characteristics of the products to perform a similarity comparison are obtained and the characteristics are combined. In vector 1 and vector 2 a count is performed for each feature in the set. Finally, the numerator and denominated are part of the cosine similarity formula, as in (1).

$$similitud(A,B) = cos(\theta) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1)$$

The cosine similarity in measures the similarity between two vectors, which is a widely used method; in this case, it allows us to determine how similar the products are based on their shared characteristics. This result will be returned to ChatGPT to continue with the response generation flow.

```python
def Calcular_Similitud(producto1, producto2):
    caracteristicas1 = [producto1['nombre'], producto1['descripcion'], producto1['categoria']]
    caracteristicas2 = [producto2['nombre'], producto2['descripcion'], producto2['categoria']]

    conjunto_caracteristicas = set(caracteristicas1 + caracteristicas2)

    vector1 = [caracteristicas1.count(c) for c in conjunto_caracteristicas]
    vector2 = [caracteristicas2.count(c) for c in conjunto_caracteristicas]

    numerador = sum(i*j for i,j in zip(vector1, vector2))
    denominador = math.sqrt(sum(i**2 for i in vector1)) * math.sqrt(sum(j**2 for j in vector2))
    similitud = numerador / denominador if denominador != 0 else 0

    return similitud
```

Fig. 4. ChatGPT Recommender

E. Product Completion

The development process for the product was successfully concluded with the implementation of the recommendation API, a critical component of the Chatbot system. As depicted in Fig. 5, the Chatbot User Interface (UI) has been carefully designed and integrated to seamlessly interact with the newly integrated recommendation API. This enhancement allows users to receive personalized recommendations, enhancing their overall experience and satisfaction with the product. The new functionality opens exciting possibilities for improved user engagement and retention, making it a significant milestone in the evolution of the product.

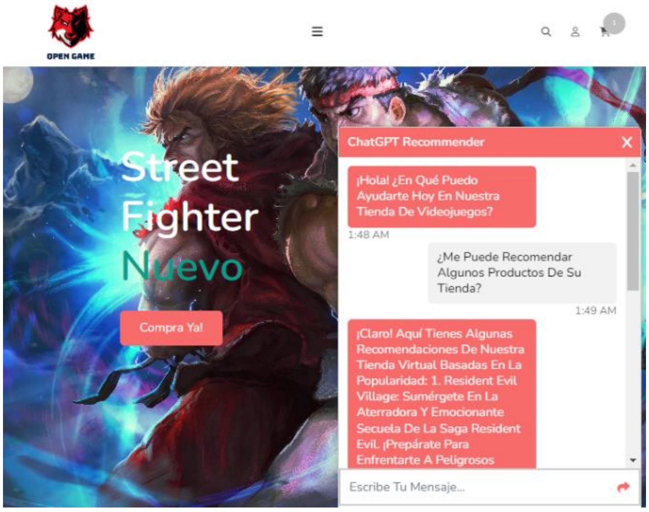

Fig. 5. ChatGPT Recommender

IV. RESULTS

The present study is a quasi-experimental investigation, so there are two groups (control and experimental). The sample was calculated with Slovin's, as in (2). It is defined that the margin of error is 5% (e = 0.05) and a population of 100 (N=100) records.

$$n = \frac{N}{1 + Ne^2} \tag{2}$$

Replacing the defined values, the sample of 80 is obtained. Then, each group will have 80 records for each indicator to be evaluated.

Hypothesis 1: The implementation of an integrated recommendation system in ChatGPT significantly improves the repurchase of users in an e-commerce store in Lima.

Table 1 indicates that the Control Group has a mean of 0.5125 since the observations had binary results (0 and 1), while the Experimental Group has a mean of 0.6875. Through the analysis of the data, we observed a mean difference of 0.175. This represents a percentage difference of approximately 34.15%. In addition, the hypothetical difference of the mean is 0 since it seeks to accept or not the hypothesis 1. Finally, the p value has a result of 0.02383812, which indicates that it is less than the significance level, which is 0.05, thus, the rejection of the null hypothesis is indicated.

TABLE I.
USER REPURCHASE RESULTS

	Control Group	***Experimental Group***
Mean	0,5125	0,6875
Variation	0,253006329	0,217563291
Size	80	80
Grouped Variation	0,23528481	
Hypothetical Difference	0	
Degrees of Freedom	158	
T-test	-2,281765972	
P(T<=t) one-tailed	0,01191906	
One-tailed critical t-value	1,654554875	
p-value	**0,02383812**	
Two-tailed critical t-value	1,975092073	

Hypothesis 2: The implementation of an integrated recommendation system in ChatGPT significantly improves the user retention rate in an e-commerce store in Lima.

Table 2 indicates that the Control Group has a mean of 0.4625 since the observations had binary results (0 and 1), while the Experimental Group has a mean of 0.7125. Through the analysis of the data, we observed a mean difference of 0.25. This represents a percentage difference of approximately 54.05%.. In addition, the hypothetical difference of the mean is 0 since it seeks to accept or not the hypothesis 2. Finally, the p value has a result of 0.0011956, which indicates that it is less than the significance level, which is 0.05, thus, the rejection of the null hypothesis is indicated.

TABLE II.
REPURCHASES OF RECOMMENDED PRODUCTS RESULTS

	Control Group	***Experimental Group***
Mean	0,4625	0,7125
Variation	0,251740506	0,207436709
Size	80	80
Grouped Variation	0,229588608	
Hypothetical Difference	0	
Degrees of Freedom	158	
T-test	-3,299854851	
P(T<=t) one-tailed	0,000597802	

	Control Group	*Experimental Group*
One-tailed critical t-value	1,654554875	
p-value	**0,0011956**	
Two-tailed critical t-value	1,975092073	

Table 3 indicates that the Control Group has a mean of 0.375 since the observations had binary results (0 and 1), while the Experimental Group has a mean of 0.55. Through the analysis of the data, we observed a mean difference of 0.175. This represents a percentage difference of approximately 46.67%. In addition, the hypothetical difference of the mean is 0 since it seeks to accept or not the hypothesis 2. Finally, the p value has a result of 0.026439335, which indicates that it is less than the significance level, which is 0.05, thus, the rejection of the null hypothesis is indicated.

TABLE III.
REPURCHASE OF PRODUCTS WITHIN A PERIOD OF 14 DAYS RESULTS

	Control Group	*Experimental Group*
Mean	0,375	0,55
Variation	0,237341772	0,250632911
Size	80	80
Grouped Variation	0,243987342	
Hypothetical Difference	0	
Degrees of Freedom	158	
T-test	-2,240703521	
P(T<=t) one-tailed	0,013219667	
One-tailed critical t-value	1,654554875	
p-value	**0,026439335**	
Two-tailed critical t-value	1,975092073	

Hypothesis 3: The implementation of an integrated recommendation system in ChatGPT significantly improves the repurchase of products in an e-commerce store in Lima.

Table 4 indicates that the Control Group has a mean of 0.8785 since the observations had binary results (0 and 1), while the Experimental Group has a mean of 0.8625. Through the analysis of the data, we observed a mean difference of 0.075. This represents a percentage difference of approximately 9.52%. In addition, the hypothetical difference of the mean is 0 since it seeks to accept or not the hypothesis 3. Finally, the p value has a result of 0.214376422, which indicates that it is less than the significance level, which is 0.05, thus, the rejection of the null hypothesis is indicated.

TABLE IV.
PRODUCTS REPURCHASE RESULTS

	Control Group	*Experimental Group*
Mean	0,7875	0,8625
Variation	0,169462025	0,120094937
Size	80	80
Grouped Variation	0,144778481	
Hypothetical Difference	0	
Degrees of Freedom	158	
T-test	-1,246634814	
P(T<=t) one-tailed	0,107188211	
One-tailed critical t-value	1,654554875	
p-value	**0,214376422**	
Two-tailed critical t-value	1,975092073	

V. DISCUSION AND CONCLUSION

The implementation of a recommendation system integrated in ChatGPT in an e-commerce store in Lima has a significant impact on the post-purchase behavior of users. This system has been shown to improve user repurchase rate by 34.15%, indicating that users who interact with the recommendation system are more inclined to engage in recurring purchases when compared to individuals who do not interact with the recommendation system. This result agrees with the work of [13] which indicates that the implementation of SR oriented to repeated purchase had an improvement of 50%; within the e-commerce community, like [14] which highlights the profitable improvement for the same e-commerce store. In addition, there is an increase in the percentage of purchases of recommended products by 54.05% and there is an increase in the percentage of purchases in a period of 14 days from the first purchase by 46.67%. This means that users who interact with the integrated SR in ChatGPT are more prone to making repeated purchases compared to those who do not engage with the innovation. this result agrees with the work of [15] which managed to observe a high level of user retention rate. Finally, the recommendation system also slightly influences the repurchase percentage of products with 9.52%, which suggests that products have a slight tendency to be repurchased which agrees with [13] to assess post-purchase behavior. This is important since it is not only necessary to evaluate the users, but also the same records of the e-commerce store, which also includes the articles.

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