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An App-Based Recommender System Based on Contrasting Automobiles

Hsiu-Wen Liu , Jei-Zheng Wu * and Fang-Lin Wu

Department of Business Administration, School of Business, Soochow University, Taipei 100, Taiwan
* Correspondence: jzwu@scu.edu.tw

Abstract: Product recommendation systems are essential for enhancing customer experience, and integrating them with mobile apps is crucial for improving usability and fostering user engagement. This study proposes a hybrid approach that utilizes comparative facts from pairwise comparison data and comparison lists, with association rules as the method to formulate the recommendation system. The study employs a dataset from the New-Cars Database app, comprising 30,867 vehicle comparisons made by 5327 users across 40 car brands and 870 cars from 30 January 2015 to 2 April 2015. Two metrics are developed to measure the system's output under varying support and confidence thresholds. The findings suggest that adjusting the support and confidence values can improve the breadth and depth of product recommendations. In addition, the unit of analysis can affect the recommendation system's output, with comparison lists supplementing and expanding the exploration of potential outcomes. The proposed hybrid approach aims to provide more reliable and comprehensive product recommendations by combining both approaches and has implications for both academic and managerial contexts by facilitating the development of effective recommendation systems.

Keywords: mobile application; recommendation system; data mining; association rule; big data

1. Introduction

Product recommendation systems are designed to help users navigate vast options and make informed decisions based on their preferences. The widespread use of recommendation systems across industries, particularly in e-commerce, highlights their potential to enhance the customer experience and drive business growth. In addition, as mobile devices continue to proliferate, integrating recommendation systems with mobile apps has become a crucial strategy for improving system usability and fostering user engagement.

Recommendation systems have been extensively researched, with various methods and algorithms developed to enhance their accuracy and efficiency [1–7]. Additionally, recommendation systems have been leveraged in a range of industries, from entertainment and retail to travel and healthcare, to provide tailored recommendations based on user's preferences, interests, and behavior [8–25]. However, despite their potential benefits, building effective and affordable recommendation systems can be a significant challenge for small app vendors with limited resources or users with limited personal data.

Our study recommends utilizing the Apriori algorithm to help small app vendors create a cost-effective product recommendation system using pairwise comparison data. Our study's novelty lies in pairwise comparison data for an item recommendation, which provides valuable insights for vendors to utilize item comparison facilities. Additionally, we explore the impact of the unit of analysis on the effectiveness of the recommendation system, which has rarely been explored in previous research. Our study conducts several experiments to observe the effects of different thresholds on recommendation outcomes, enabling vendors to gain insights into the system's performance. Finally, to measure the effectiveness of the recommendation system, we introduce two useful metrics, namely the breadth and average depth. Specifically, this study aims to answer three research questions:

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1. How can pairwise comparison information be used to develop a product recommendation system for small app vendors?
2. What is the impact of the unit of analysis on the effectiveness of the recommendation system?
3. How can small app vendors measure the effectiveness of the recommendation system using proposed metrics, namely the breadth and average depth?

This study contributes to the field of recommendation systems by proposing a hybrid approach that utilizes pairwise comparison data and association rules to develop a product recommendation system for small app vendors. Our findings can assist small app vendors with limited resources in creating a cost-effective recommendation system and improving their competitiveness in the market. Moreover, our proposed methodology can be applied to various industries, making our study relevant for both academic and managerial contexts.

The following sections provide a literature review that outlines the various categories and techniques related to product recommendation. This review contextualizes our study and provides a foundation for our proposed hybrid strategy. Following the literature review, we present the case and data we collect, as well as the two metrics we propose to assess the effectiveness of our recommendation system. Finally, in the discussion section, we propose our hybrid strategy incorporating insights from our association rule analysis. To visually represent our proposed framework, we include Figure 1, which illustrates the flowchart for our hybrid strategy.

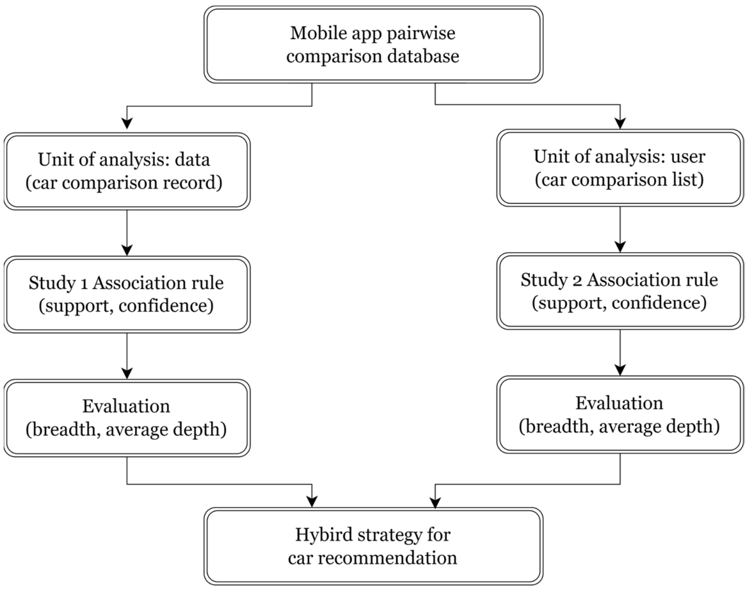

Figure 1. Recommender system based on pairwise comparison data.

2. Literature Review

In this literature review, we analyze various types of recommendation systems and the concepts behind them. Recommendation systems can be classified based on their purpose, the type of data they use, the level of personalization, and the methods used to generate recommendations. This analysis employs the Apriori algorithm to construct a recommendation system. Apriori is a non-personalizing, item-based, and discovery-based procedure for mining association rules and falls under the category of collaborative filtering.

2.1. Discovery-Based versus Decision-Based Recommendations

The purpose of a recommendation system can be categorized as either discovery-based or decision-based. Discovery-based recommendation systems are designed to help users explore new items and find related products; this includes suggesting items similar to what the user is currently looking at or items that other users with similar interests have purchased or viewed. This system helps users explore new items that they may not have otherwise known.

Decision-based recommendation systems, on the other hand, are aimed at helping users complete specific tasks that they have already identified as relevant to their needs. They are designed to help the user make an informed decision about the item they are currently seeking. This system can provide the user with detailed information about the item, such as price comparisons, customer reviews, and ratings. This system can also suggest items similar to the item the user is currently looking at but with better features or a lower price. For a recommendation system to be effective, it can provide discovery-based and decision-based recommendation systems to provide users with the best possible operating experience.

2.2. User-Based versus Item-Based Recommendations

The type of data a recommendation system is built on can be either user- or item-based. User-based recommendation systems focus on the user's past interactions and behaviors to make recommendations [26,27]. These interactions and behaviors include the type of items the user has previously purchased or viewed, the amount of time the user has spent viewing or interacting with a particular item, the ratings or reviews that the user has given to an item, and the user's interactions with other users. By analyzing user behavior and past interactions, user-based recommendation systems can tailor personalized recommendations to the individual user.

On the other hand, item-based recommendation systems analyze similar items to make recommendations [28–31]. These systems examine the characteristics of items similar to the ones that the user is viewing or interacting with and recommend additional items with similar characteristics. For example, a recommendation system might suggest additional books based on the author, subject matter, or genre if a user is viewing a particular book. By analyzing the characteristics of similar items, item-based recommendation systems can suggest items similar to the one the user is currently viewing, thereby providing the user with more relevant recommendations. Both types of recommendation systems offer a variety of benefits and can be used to make relevant recommendations for individual users.

2.3. Personalizing versus Non-Personalizing Recommendations

One of the most important challenges in recommendation systems is deciding whether to customize recommendations for a particular user or to make non-personalized recommendations that are more general [32]. Personalized recommendations are based on the individual's unique characteristics, whereas non-personalized recommendations are based on a larger data set. Therefore, one way of categorizing recommendation systems is to look at the level of personalization, the extent to which a recommendation system is tailored to the individual user or the extent to which a recommendation system is tailored to the individual user. There are three levels of personalization in recommendation systems: customization, customization with social influence, and customization with social influence and explicit feedback. Customization refers to a recommendation system personalized to the user's past behavior. Customization with social influence refers to a recommendation system that is personalized to the user's past behavior and considers the user's relationships with others. Lastly, customization with social influence and explicit feedback refers to a recommendation system personalized to the user's past behavior, relationships with other people, and the user's explicit feedback on the items they have tried and tested.

Several studies have explored the benefits of personalized recommendations [11,12,14,15,22,25,27,33]. However, there are also advantages to non-personalized recommendations, particularly when the user has limited data available or when a general recommendation is sufficient [34]. Ultimately, whether to personalize recommendations depends on the specific goals of the recommendation system and the available data.

2.4. Techniques for Generating Recommendations

In this section, we discuss various techniques for generating recommendations, which can be broadly classified into eight categories and further classified into content-based filtering, collaborative filtering, hybrid, or other heuristic approaches.

Data Mining Techniques

Data mining techniques are used to uncover patterns and rules in large datasets [35]. Scientists have used this technique to improve the performance of recommender systems. These techniques can be broadly classified into eight categories: association rule, clustering, decision tree, K-nearest neighbors, link analysis, neural network, regression, and other heuristic methods [36]. In addition, they can be classified according to their techniques as content-based filtering (CBF), collaborative filtering (CF), hybrid, or other heuristic approaches.

1. Content-Based Filtering

Content-based filtering builds portraits of users and items by analyzing extra information, such as user–item profiles and content [37,38]. However, it is often hard to obtain useful information to construct the portrait, which limits its practical applications and efficacy.

2. Collaborative Filtering

Collaborative filtering is built on the user's behavior, either the items they have interacted with or the items that other people with similar interests have interacted with [30,39]. A collaborative filtering algorithm can provide precise recommendations based on user and item interactions, including browsing, rating, and clicks. It is often used to create recommender systems, with association rules and K-nearest neighbors (KNN) being two popular implementations [36].

3. Association Rule Mining

Association rule mining is an unsupervised learning algorithm that frequently searches for relationships between items that occur together in user interactions. This technique discovers all relationships between items in a dataset that meet a user-defined minimum support and confidence threshold. For example, this process looks for relationships in the form of $X \rightarrow Y$, where X and Y are both sets of items. The approach involves setting a minimum support and confidence threshold, which is used to filter out weak associations. Association rule mining is often used to generate recommendations in business applications, where it is used to identify items that are frequently purchased together and recommend them to users. This technique has also been used in other applications, such as web mining [40], where it is used to identify patterns in user online behavior to provide web personalization services.

4. K-Nearest Neighbors

The K-nearest neighbors (KNN) algorithm is a supervised learning algorithm commonly used in recommender systems that rely on user–item interactions. This approach involves representing the user's ratings for various items in a matrix format, in which each cell corresponds to the rating of a specific item by a particular user. KNN is based on similarity and aims to classify an unknown sample by identifying the K closest known samples and assigning it to the class with the most frequent occurrence among them. The algorithm computes the similarity between the target user and all other users in the system. It then selects the K most similar users and leverages their ratings for items the target user has not interacted with to generate recommendations. KNN has been widely used in various applications and has shown strong performance in numerous recommender system scenarios [41,42].

5. Hybrid or other Heuristic Approaches

Hybrid or other heuristic approach recommendation systems utilize different approaches to provide recommendations [43–45]. The hybrid recommender is particularly helpful in addressing the new user problem. Hybrid systems may use collaborative filtering, natural language processing, or deep learning algorithms [46–50]. It may also use other data sources like user ratings and reviews to inform its predictions.

2.5. Summary of the Literature Review

Previous studies have mainly focused on personalized recommendations by accumulating large amounts of consumer data, such as ratings or reviews. However, association rule mining is a data mining technique that can be applied effectively in situations with limited user information, e.g., purchasing durable goods like cars. Based on our research findings, we propose a hybrid approach that can enhance the effectiveness of association-rule-based recommendation systems and improve the user experience. These findings provide valuable insights for businesses to improve their product recommendation systems and for future research in this field.

3. Method

3.1. Data

This study employs pairwise comparison records from Taiwan's New Cars Database mobile app. The data include 30,867 vehicle comparisons from 5327 users across 40 car brands and 870 cars from 30 January 2015 to 2 April 2015. The app was launched in December 2013, providing users with comprehensive information on cars, including details, specifications, a media database with high-quality photos and videos, and up to 20 test drive reports every month. The app collaborates with well-known car media, websites, and magazines, providing users with more than 100 car news and market dynamics every month to ensure comprehensive and real-time news exposure. The app owner has focused on the total user experience, offering a friendly and smooth user interface. The company also facilitates the exchange of car-related information, such as advertisement, second-hand car selling, and remodeling, to build a car-related information platform. The browsing and comparison data are stored in a cloud database, which provides valuable data for big data analysis.

3.2. Settings

This recommender system allows users to compare the attributes of two cars side-by-side, generating a table with relevant information. Association rules [51,52] are employed to analyze pairwise comparison records and build the recommender system. Each time a user compares one car (e.g., C001) to another (e.g., C002), the comparison is registered in real-time and considered an individual record. Three conventional metrics, namely support, confidence, and lift, are utilized to establish appropriate thresholds for effective association rules. In this study, the users' car comparison records are divided into two units of analysis for comparison: study 1 includes 30,867 car comparison records, and each comparison made during the click process is treated as one record; study 2 includes 5327 user comparison lists, and each list of comparison is treated as one record.

3.3. Measures for Evaluating the Association Rules for Recommendation

A key challenge in utilizing the Apriori method in a recommendation system is establishing appropriate thresholds for generating effective association rules. In the context of product recommendations for sales purposes, thresholds are typically set at higher levels, such as high support, high confidence, and lift values greater than 1, to identify related products for bundle sales and increase revenue per customer. However, this study focuses on recommending at least one vehicle from a total of 870 vehicles. Therefore, the thresholds are adjusted through experiments to determine the number of recommended vehicles from the total pool.

Two main criteria are developed to evaluate the effectiveness of the association rules generated for recommendations: (1) recommendation breadth and (2) average depth (i.e., the average number of associations per car). In addition, these two criteria are used to evaluate the results of adjusting the support and confidence thresholds.

$$Breadth = n/N \times 100\% \quad (1)$$

$$\bar{D} = \frac{\sum_{i=1}^{n} X_i}{n} \times 100\% \quad (2)$$

Recommendation breadth is measured as the proportion of cars with recommended vehicles compared to the total number of vehicles, as shown in Equation (1), where n is the number of cars with associated products and N is the total number of cars in the database. The value is between 0 and 1, with a higher breadth indicating a wider range of recommended vehicles. If the breadth is 100%, every vehicle has its recommendations. The average depth $\bar{D}$ is defined as the ratio of the total number of association rules to the number of cars with recommended vehicles, as shown in Equation (2), where i is the index of the car and Xi is the number of associated products with a given car i. A higher average depth indicates that a given vehicle is linked to more cars due to the association rules.

4. Result

4.1. Findings of Study 1

4.1.1. Settings and Evaluation

The results of this study show that adjustments in the support and confidence thresholds significantly impact the number of association rules generated and the breadth and average depth of the recommendations (Table 1).

Table 1. Study 1: Association rules with various settings.

ID	Support		Confidence	Rules	Vehicle	Breadth	Average
	(%)	(Count)	(%)	Count	Count	(%)	Depth
1	0.200	61	20	27	32	3.68	0.84
2	0.035	10	20	217	271	31.15	0.8
3	0.035	10	10	515	332	38.16	1.55
4	0.035	10	5	755	334	38.39	2.26
5	0.017	5	20	855	420	48.28	2.04
6	0.017	5	10	912	512	58.85	1.78
7	0.017	5	5	1419	514	59.08	2.76

Seven different threshold settings are tested, with the first setting used as a benchmark for comparison. The results indicate that selecting settings above the second case is necessary for obtaining a broader breadth in the recommendations. In the sixth case, the support and confidence thresholds are set at 0.017% and 10%, respectively, resulting in 512 recommended vehicles and 912 association rules. By slightly adjusting the confidence threshold in the sixth setting, a more effective outcome is obtained than that of the fifth setting in terms of breadth while maintaining a similar average depth.

Furthermore, the seventh case shows that reducing the confidence threshold can increase the average depth of the recommendations by almost one. However, this comes at the cost of lower confidence, with only 5% of people who choose product A also choosing product B when the confidence threshold is set at 5%. Therefore, a confidence threshold of 10% is chosen. Additionally, the support threshold should not be set below 0.017%, as this results in a support count of less than 5. Overall, Table 1 reveals that adjustments in the support threshold affect breadth, whereas adjustments in the confidence threshold have a negligible effect on breadth but a detectable effect on average depth. Therefore, the sixth setting is chosen for this study, and the outcomes are reported in Table 2.

Table 2. Association rules illustration.

ID	Association Rules	Support	Confidence	Lift
1	{MA3 4L} => {MA3 4M}	0.74%	31.34%	8.96
2	{MA3 5L} => {MA3 5M}	0.73%	30.92%	8.30
3	{FD K 2L-F} => {FD K 2L-D}	0.70%	22.80%	11.25
4	{MA3 4S} => {MA3 4L}	0.62%	29.83%	12.55
5	{MA CX-5 SKY-D AWD} => {FD K 2L-D}	0.61%	22.47%	7.36
6	{MA CX-5 SKY-D 2WD} => {MA CX-5 SKY-D AWD}	0.42%	22.22%	8.61
7	{MA3 4S} => {MA3 4M}	0.41%	19.78%	5.66
8	{FD 5 SPORT} => {MA 5L}	0.37%	15.11%	4.05
9	{FD 5 SPORT} => {FD 5 Classic}	0.35%	36.24%	14.71
10	{FD 5 EcoBoost } => {HODA FIT S}	0.32%	17.67%	9.26

4.1.2. Illustration and Recommendation Aids for a Car Info App

Table 2 shows the top 10 association rules with the highest support values, which provide important insights into the relationship between different vehicle features. For better diversity, the results exclude the same pairings. In this table, the rules presented in this study offer diverse suggestions for users seeking to make informed decisions about their vehicle preferences. The support value indicates the frequency of occurrence of each rule, whereas the confidence value suggests the likelihood of a user selecting a certain vehicle after considering another. The lift value indicates the strength of the association between two items, with a value greater than 1 suggesting a positive correlation. For example, rule 3 indicates a strong association between {FD K 2L-F} and {FD K 2L-D}, with a support value of 0.70%, suggesting that users frequently compare these two features. The confidence value of 22.8% further confirms this association, indicating that users who select {FD K 2L-D} have a 22.8% chance of also selecting {FD K 2L-F}.

Moreover, the lift value of 11.25 indicates a strong positive correlation between these features. Notably, rules 5 and 8 suggest comparing two different brands, which can give users a broader perspective when making their purchasing decisions. By offering these valuable insights, the car information app can help users identify their preferred vehicle features and ultimately enhance their loyalty to the platform. These findings highlight the importance of leveraging association rule mining to uncover meaningful insights from large datasets, which can inform decision-making and improve the user experience in various applications.

4.2. Findings of Study 2

4.2.1. Settings and Evaluation

In this study, the initial threshold settings are established at 1% support and 20% confidence, then adjusted based on the findings. Table 3 presents a summary of eight different threshold settings.

Table 3. Association rules with various settings.

ID	Support		Confidence	Rules	Vehicle	Breadth	Average
	(%)	(Count)	(%)	Count	Count	(%)	Depth
1	1	53	20	78	36	4.14	2.17
2	0.2	10	40	1,414	272	31.26	5.19
3	0.2	10	30	1,936	322	37.01	6.01
4	0.2	10	20	2,740	333	38.28	8.23
5	0.2	10	10	4,032	333	38.28	12.1
6	0.1	5	30	11,802	507	58.28	23.3
7	0.1	5	20	14,786	523	60.11	28.3
8	0.1	5	10	19,059	523	60.11	36.4

In Table 3, the first setting presents the baseline setting for the experiment, which uses a support level of 1% (Frequency = 53) and a minimum confidence level of 20%. This setting yields a total of 78 association rules and 36 recommended vehicles. To increase the breadth of recommendations, settings with greater thresholds than that of the second case are chosen. The seventh case, in which the support and confidence parameters are set at 0.1% and 20%, respectively, results in 523 vehicles with recommended vehicles and 14,786 association rules. A minor adjustment to the confidence in the seventh setting is more effective than the sixth setting in terms of average depth, with the average depth of recommended products increasing by nearly five. However, it should be noted that a higher depth may not necessarily be beneficial to users because it can lead to a heavy load and decreased reliability of advice. It is also important to mention that a support threshold below 0.1% may not be practical, as its support count is less than five. Table 3 demonstrates that the adjustment to the support level affects the breadth of recommendations, whereas the confidence level below 30% has a minor effect on breadth but a noticeable result on average depth. As a result, the seventh setting is chosen for this study, and the results are presented in Table 4.

Table 4. Association rules illustration.

ID	Association Rules	Support	Confidence	Lift
1	{MA3 5L} => {MA3 5M}	3.83%	58.45%	6.43
2	{MA3 4L} => {MA3 4M}	3.19%	62.27%	8.57
3	{MA3 4S} => {MA3 4L}	2.97%	55.24%	10.78
4	{FD K 2L-F} => {FD K 2L-D}	2.65%	58.02%	10.13
5	{MA3 4S} => {MA3 4M}	2.65%	49.30%	6.79
6	{MA3 CX5 D 2WD} => {MA3 CX5 D AWD}	2.42%	42.72%	9.72
7	{MA3 4M} => {MA3 5M}	2.29%	31.52%	3.47
8	{FD 5 SPORT} => {MA 5L}	2.10%	39.30%	4.33
9	{MA3 4L, MA3 4S} => {MA3 4M}	1.82%	61.39%	8.45
10	{MA3 CX5 G 2WD} => {MA CX-5 D 2WD}	1.78%	33.83%	6.32

4.2.2. Illustration and Recommendation Aids for a Car Info App

Table 4 presents the top 10 association rules sorted by support using the seventh case setting (support = 0.1% and confidence = 20%). The results highlight relevant anonymous records of association rules and exclude the same pairings for better diversity. For example, rule 8 indicates a relationship between {FD 5 SPORT} and {MA 5L} with a support value of 2.1%, suggesting that, out of 5327 users' comparison history records, approximately 112 of them are associated with the comparison of these two items ($5327 \times 2.1\% = 112$). Furthermore, the confidence of 39.3% indicates a 39.3% likelihood that, if a user considers {FD 5 SPORT}, they will select {MA 5L}. The lift value of 4.33, greater than 1, suggests that {FD 5 SPORT} and {MA 5L} are positively correlated. Rules 1–7 and 9–10 all demonstrate comparisons between the same brand. With the aid of these rules, users can quickly identify their preferred vehicle and become more committed to using the car information app.

The results from Table 4 provide valuable insights into the association rules of vehicle comparisons. The findings from this research can assist users in identifying their preferred vehicle and improve the overall user experience of the car information app. Additionally, these results can provide useful information for the automotive industry in understanding customer preferences and improving marketing strategies.

5. Discussion

5.1. A Hybrid Strategy for Product Recommendation

The study revealed that the recommendation system based on comparison record data had a shallow average depth of 2.5 (Study 1), whereas the system based on comparison lists had a much deeper average depth of 28 (Study 2). However, while the comparison records provided precise information about the compared product, the comparison lists allowed for exploring more potential outcomes. Therefore, a hybrid product recommendation strategy was developed to combine both sets of recommendations, resulting in a more reliable and comprehensive hybrid recommendation system that aims to increase consumer engagement.

The hybrid strategy utilizes two approaches: the first suggests "people who examined this item also looked at" and provides one or two options for consumers to consider. The second approach provides a comparison list recommendation, as observed in Study 2, which presents a list of choices for consumers who wish to explore further. By leveraging both approaches, the hybrid system can provide more outcomes and cater to the diverse requirements of users, especially those who may lack expertise in making decisions.

In summary, the proposed hybrid product recommendation strategy can provide users with more options and assist them in making informed purchase decisions. Furthermore, this approach addresses users' diverse requirements and helps them make better purchasing decisions.

5.2. Theoretical Implications

Our study represents a novel approach to utilizing pairwise comparison data within the context of recommendation systems. The results demonstrate that this type of data can be effectively leveraged to generate product recommendations through collaborative user intelligence, which in turn can help customers identify suitable products. Our research introduces two new metrics that can be used to assess the outcomes of recommendation analysis and guide producers in selecting appropriate threshold values for parameter settings. By adjusting the support value, the breadth of the recommendation can be increased, resulting in greater coverage of products. By adjusting the confidence value, the average depth of product recommendation can be improved, forming more correlated associations for each item. These findings have significant implications for both the theoretical and practical aspects of recommendation systems.

5.3. Managerial Implications

The findings of this study have significant implications for app developers and small businesses that lack the necessary resources and expertise to develop professional product recommendation systems. Specifically, association rule analysis can provide a cost-effective method for generating optimal product suggestions based on pairwise comparison data. Moreover, the hybrid strategy proposed in this study considers consumer needs when comparing products, which can assist customers in making better purchasing decisions. One of the key advantages of utilizing pairwise comparison data for recommendation systems is the ability to accumulate comparison records that provide rich value to consumers, app developers, and car manufacturers. These data can be analyzed, leading to a better understanding of consumer preferences and needs.

Therefore, the practical solutions proposed in this study can help small businesses and app developers provide effective product recommendations and enhance their competitiveness in the market. Furthermore, by adopting the hybrid approach and utilizing the insights gained from this study, these organizations can improve their product offerings and better meet the needs of their customers.

5.4. Future Research Directions

Although our study provides valuable insights into the use of pairwise comparison data to generate product recommendations, there are still areas that require further exploration. One direction for future research is to investigate the potential of incorporating other forms of data, such as text and image data, into the analysis to enhance the product recommendations' accuracy further. Additionally, it would be beneficial to examine the effectiveness of the proposed hybrid strategy in different industries and for different types of products. Another possible avenue for future research is to explore how machine learning algorithms can be utilized to improve the efficiency of the association rule analysis and enable real-time product recommendations. Furthermore, future research can focus on developing recommendation systems that consider individual users' experiences, grasping how people deal with product recommendations.

Future research can further explore how businesses can utilize customer feedback to enhance the effectiveness of product recommendation systems. By surveying customers' satisfaction with their purchases and experiences with the company, businesses can generate customer ratings that inform their product recommendations. Additionally, businesses can consider the experiences of their peers to inform them of the types of products they recommend. Moreover, future research should continue to prioritize considering the customer experience to ensure that product recommendations meet individual needs and preferences. Further exploration of these areas can better understand the potential and limitations of product recommendation systems and help businesses better serve their customers.

6. Conclusions

In this study, we set out to investigate how pairwise comparison data can be utilized to generate product recommendations. Our results from two studies demonstrate the effectiveness of using association rule analysis to extract meaningful insights from pairwise comparison data and generate product recommendations for individual consumers. We propose two evaluation metrics, breadth, and average depth, to aid businesses in selecting appropriate parameter settings for their recommendation systems. Additionally, we develop a hybrid product recommendation strategy that can provide valuable managerial implications for vendors seeking to improve customer satisfaction. Our findings offer significant potential for businesses to save time and resources while delivering relevant product suggestions to customers. Overall, this study contributes to the growing body of research on recommender systems and provides practical insights for businesses seeking to leverage pairwise comparison data to enhance their product recommendations.

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