An Adaptive Hybrid Recommender System Standard for Personalized Intelligent E-Business Ecosystems.

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ABSTRACT

This research aims at investigating how recommender systems standard can improve user experience and business performance in intelligent e-businesses. The study has examined the impact of recommender systems algorithms as well as their limitations. It attempts to identify important aspects which constitute the standard architecture of these systems within e-commerce environments. A mixed methods approach together with a combination of quantitative analysis of user behaviour data collected from an e-commerce platform and qualitative insights from user surveys or interviews has been employed by the study. Using this method, it aims to assess effectiveness of recommender systems and influence on purchase behaviour. The analysis of user behaviour data reveals patterns in user interactions with recommender systems, including click-through rates, conversion rates, and average order value. The qualitative insights obtained through user surveys and interviews provide valuable feedback on user satisfaction levels, perceived usefulness of recommendations, and areas for improvement in the recommender system design. The study concludes that recommender systems play a crucial role in driving user engagement and enhancing the overall user experience in e-commerce environment and there is no specific dedicated standard for the recommender system.

Keywords: Recommendation Systems, E-commerce, Intelligent Systems, Standardization

INTRODUCTION

In this competitive world, information and communication technology (ICT) has expanded and increased in proportion to the advancement of effective product and service delivery (Ugwu, N. V., & Udanor, C. N. 2021). Unfortunately, it is still more and more thorny and time-consuming to filter and deliver the information needed in e-commerce stores such as the ones available on the Internet due to data explosion (Ju, C., & Xu, C. 2013).

Nowadays, the Internet has become the de facto digital market, and ways must be found to mine and filter genuine content to encourage privacy and accuracy and to enhance information-delivering activities. Due to the challenges posed by e-commerce platforms by competitors, many service providers have deemed it fit to offer their customers the trendy internet tools to facilitate their acquisition of more information and knowledge about the goods and services of their predilection. For service providers to succeed in their customers' fidelity, confidence, and trust in providing goods and quality services of their choice and to increase their business profits, the internet tools should be investigated, evaluated, protected, and also made available for easy sharing of sensitive information and opinions, either between the customers or between the customers and the service providers using the tools (Ugwu, N. V., & Udanor, C. N. 2021). To this effect, researchers from the business environment have investigated the e-business platform and advocated the concept of data privacy (one-to-one) in marketing (Sarwar, B. et al, 2000), and this concept calls for the usage of technological systems to help organizations care for customers individually and also to monitor customer behaviour data for online purchasing as well as make timely predictions about changes in the industry.

To succeed in an increasingly challenging internet marketplace, and to overcome data overload in e-commerce stores, a recommender system was introduced. It is an aspect of artificial intelligence, as well as a subclass of information filtering structures. It came into prospect as a self-ruling study section within the mid-nineties while researchers initiated the idea to resolve the recommendation problems that depend upon the rating structure (Lu, J. et al 2015; Adomavicius, G., & Tuzhilin, A. 2005; Strömqvist, Z. 2018; Pu, P. et al. 2011). The recommender system is an efficient methodology and tool to cushion the dilemma of data overload. It mines and filters the fascinating items in an e-commerce store, (Ju, C., & Xu, C. 2013; Martin, K. D., & Murphy, P. E. 2016; Recommender system. n.d), and also, facilitates the information filtering process that suggests the most accurate products to meticulous customers'. It predicts the products that will interest customers by looking at both the product-related information and the customer's profile. Not only this helps in selecting the right goods for individuals but also contributes to cross selling by suggesting extra items to customers so as to retain them. This is due to that fact that people tend to go back to websites which offer them more of their requirements.

However, accuracy has always been the research aim of recommender systems to enhance the intelligent e-business recommender standard. It should not only encompass and encourage only high accuracy but additionally include transparency, privacy, variety, and explainability. These properties assist in remodeling the widespread architectural performance of a recommender system.

Recommender systems leverage detailed personal information about users' tastes to provide accurate recommendations. Ratings, consumption patterns, and individual profiles are a few examples (Recommender system. (n.d.). To ensure accurate recommendations, the recommender system service providers gather data whenever feasible. The information is collected implicitly or explicitly from the loyal consumers for investigating the recommender system performances and the impact of the recommender system on their user's experience, which will help the service provider in decision-making to improve the standard of their algorithms which may lead to increasing income. However, privacy is a matter of interest since customers may perhaps not been willing to share their sensitive preferences with the service providers (Pu, P. et al, 2011). The possible threats to user privacy are frequently underrated when automatically tampered without the users' knowledge. The threat to an individual's privacy may affect or alter the standard accuracy of the recommendations.

Investigating the standard of the recommender system necessitates attention at every stage of the system life cycle, including design and development as well as ongoing operation and improvement (Pu, P. et al, 2011). Ensuring excellent delivery is a prerequisite for a system's practical success. The investigation may assess a system's fundamental functionality in its purest form or it may examine and survey the system's usage within its broader context. The essential motivation driving the improvement of the recommender system is to lessen data burden and handling cost by dealing with personalized data and information through investigation of the interests behaviour of the users to understand his/her feelings about the products.

Moreover, the objectives of this work are to comprehensively investigate the e-business recommender systems standard with a focus on their algorithms and their limitations, their uses, and their impact on user experience, and business outcomes, with the view of providing an open standard architecture across all application, which could be deployed to enhanced businesses. Each service provider might make the effort to benefit to improve their clients' pleasure and retention.

Artificial intelligence in e-commerce.

Due to the rapid changes in the digital landscape of today, companies are always searching for new and creative ways to increase productivity, efficiency, and customer satisfaction. Artificial intelligence (AI) is the alternative remedy that has been increasingly popular in recent years. However, Using AI systems, tools, techniques, or algorithms to enable online purchasing and selling of goods and services is known as artificial intelligence (AI) in e-commerce (Bawack, R. E. et al, 2022). It plays a vital role in many leading information and business systems. Its contribution is presently urgent in non-deterministic frameworks, for example, work process, information mining, creation planning, production network strategies, recommendation and most as of late, online business (e-commerce). It has revolutionized several industries with its capacity to analyze massive volumes of data and generate insightful predictions and recommendations.

AI according to Alabi, O. B., & Funmilola, A. O. (2021), has revolutionized global online shopping and opened up new avenues for e-commerce businesses to provide customers with improved services such as recommendations. With AI, it's now possible to provide customers with virtual personal shoppers and individualized experiences when purchasing (Alabi, O. B., & Funmilola, A. O. 2021). It is constantly evolving the online purchasing encounter for vendors and customers by offering fresh approaches to the big data that are accessible and allow online retailers to engage with their customers in a whole new way. And also create exceptional customer experiences. With AI, e-retailers can easily fetch customer data, analyze it to forecast future purchasing trends and provide product recommendations by utilizing customers' purchasing habits. Fraudsters attack e-commerce platforms and enterprises. On the other hand, systems for detecting fraud powered by AI can lessen the possibility of illicit transactions. These systems can trace fake IP addresses, identify consumer activity trends, and analyze them.

Investigation of recommender system standard

Recommender systems are becoming essential to many online platforms since they help customers find relevant products and improve user experience (Alabi, O. B., & Funmilola, A. O. 2021). However, When developing recommender systems, there is a lack of standard procedures, which makes it difficult to guarantee system fairness, performance, user privacy, trust and transparency. From examination of business experiences, this investigation seeks to explore the current status of several types of recommender system standards. Nonetheless, there are several reasons why researching recommender system standards is crucial. It contributes to ensuring the correctness and dependability of user recommendations. The industry can develop best practices and recommendations that advance the efficacy and quality of recommender systems by defining standards. It is vital for resolving confidentiality and principled issues. Standards can offer guidance on how to handle user data, guarantee fairness and openness in the recommendation process, and protect user privacy.

Moreover, investigating recommender system standards encourages invention and rivalry in the business. Standards encourage scholars and specialists to create innovative algorithms and strategies that might enhance the performance of recommender systems by establishing uniform benchmarks and evaluation measures. In this work, we are investigating to comprehensively understand if there is a particular standard specified for the performance of the e-commerce recommender system which will help to providing an open standard architecture across all application, which could be deployed to enhanced e-businesses.

Algorithmic Logical relationship in recommender system approach

In an intelligent recommendation system, the term "logical relationship" refers to the underlying method or algorithm used to determine which products or contents to recommend to users. This relationship is crucial for making personalized and relevant recommendations. The logical relationship represents the fundamental logic or mechanism that connects user preferences and historical behaviour with the products or contents that are suggested to them. It is like the decision-making process that takes place behind the scenes to provide users with recommendations tailored to their tastes and needs.

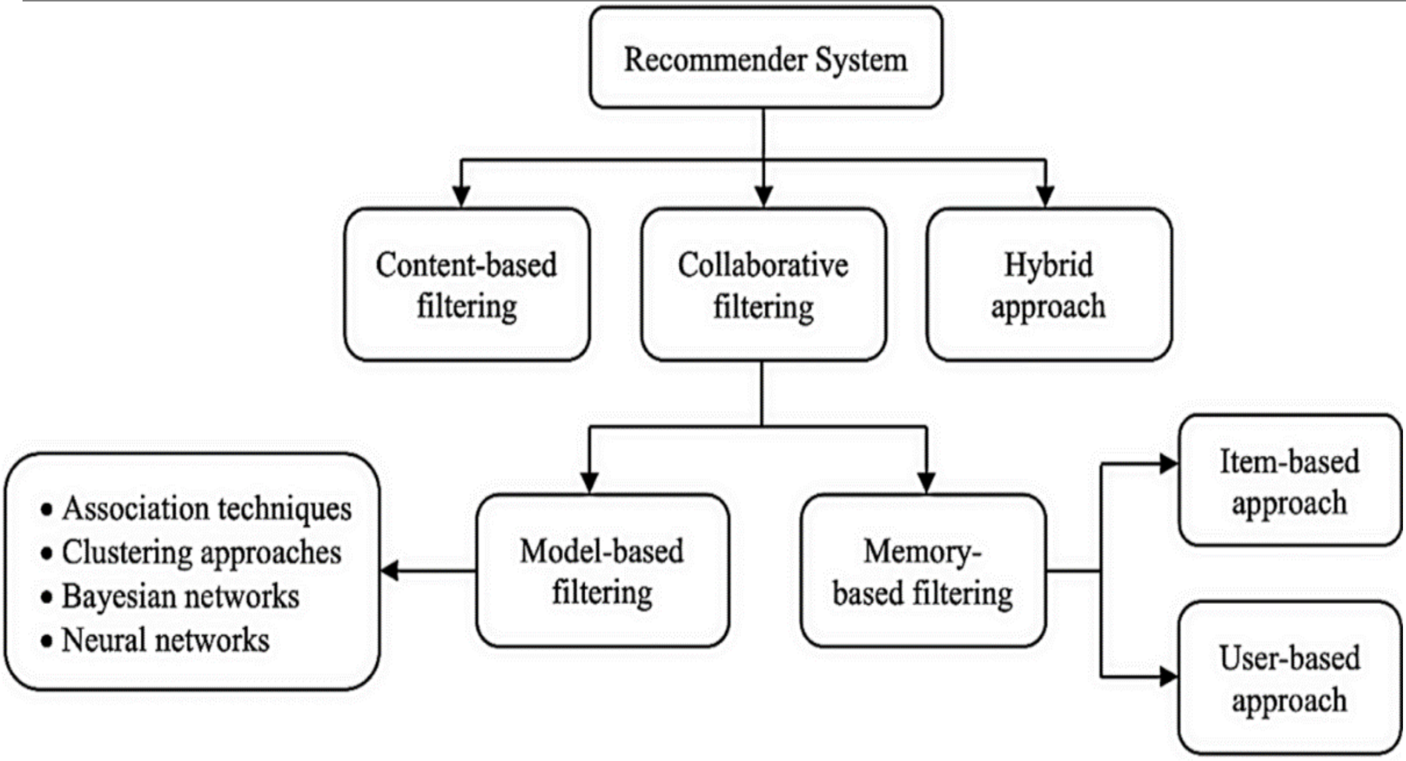

Fig.1 recommender filtering technique (Roy, D., & Dutta, M., 2022).

This logical relationship can take various forms, depending on the type of recommendation system and the algorithms it employs:

Content-based filtering algorithm: The attributes of items the customer is akin to are regarded as "contents". This is a type of recommender system algorithm that logically depends on the information provided by the customers about a particular product. It is based on calculating and analyzing the affiliation between the attributes or features of products and also comparing them to the profile of the customer that accesses the products. In this system, the general and the standard method of operation is that it uses the customer feature (customer's purchase history), the attributes of items or their ratings to recommend to the customer what he/she might want to purchase in the future (Pu, P. et al, 2011). For content-based strategies, a metric, for example, TF–IDF (term frequency–inverse document frequency), can be applied (Madhusree, K. et al, 2020).

The three stages of the content-based filtering technique are summarized under the following; item representation: Information is taken out in the item representation stage to construct features of item. It generates the representation of the structured object. The creation of a user profile comes next. The user profile is derived from past actions, such as like or dislike an item, rating it, or examining a written remark (review) the consumer left for a certain item. This phase is referred to as "learning the user profile step." And the recommendations generator is the last but certainly not least stage. This stage generates a list of suggested products and compares them with the attributes of the user's profile (AL-Ghuribi, S. M., 2019). However, serendipity issues, new user issues, and restricted content analysis issues are some of CB's drawbacks or limitations (Ricci, F., et al. 2010). This method works best in domains like movie and music recommendation where comprehensive attribute data is accessible.

Collaborative filtering: this is the most popular approach used to generate RSs (Yang, C. et al,2016). The general and standard methods used by collaborative filtering are the nearest neighbour-hood algorithm (KNN) and matrix factorization (MF), etc. The former is using to find the relationship between users' predilections (Das, S. 2015, August 11). While the letter is using as the inference model to uncover user and item latent representations whose linear interaction explains observed feedback. However, the collaborative filtering logical relationship is grounded in the concept that people who granted the same offer in the past will grant the same offer in the future, which means that they will have the same preferences on similar kinds of items as they had in the past (Pu, P. et al, 2011).. Therefore, it uses the group user behaviour to predict other users. The collaborative filtering approach's ability to recommend complicated objects like movies accurately without requiring an "understanding" of the item itself is one of its main advantages in collaborative filtering. This is because it does not rely mainly on machine-analyzable material. Collaborative filtering techniques are classified into **memory-based and model-based** (Chen, L., et al., 2015

Memory-based: This is a type of modus operandi that is normally applied to unrefined data with no dispensation. They are simple for execution along with the resultant suggestion that is normally simple to clarify. Moreover, memory-based techniques are further classified into user-based and item-based.

User-based collaborative filtering: this is a type of filtering algorithm that lies on the postulation that said, show me your friend and I will tell you who you are. The system will be interested in calculating the similarities between the target users. The satisfaction of a particular user depends on the general view of other users in the same cluster.

Items-based collaborative filtering: this is a type of filtering algorithm that depends on the user's rating. That is, if Mr A and Mr B rated books, for example, Things Fall Apart and Arrow of Gods, said 5-star rating, however, if Mr C buys Things Fall Apart, there is a likelihood that the book titled, arrow of Gods will be recommended to Mr. C, since the system will recognize the books as related based on user rating. Though, in this view, it is revealed to implement the user-based and items-based collaborative filtering, the likeness between the items-based is firmer than the likeness between the users-based collaborative. This is because the books titled Things Fall Apart and Arrow of Gods will forever remain the same but human beings change his or her minds at any time. That is why contextual information is highly important in the course of the implementation to improve the standard presentation of the recommender system. The two methods that are commonly used in finding the similarity between users/items are the Pearson correlation and the cosine-based methods (Ugwu, N. V., & Udanor, C. N. 2021).

Model-based collaborative filtering: this is among the machine learning methods for creating recommendations or suggestions. In this method, one of the similarity measurements is used to calculate how alike the items are in the data set, and later these similarity values shall be used to predict scores of user-item pairs that are not present in their respective datasets (Kaur, H., & Bathla, G. 2019).

knowledge-based recommendation filtering: This method is used in some situations where neither the content-based nor the collaborative techniques can function well since there are not enough ratings available for a particular item, which has an impact on the recommendation process (AL-Ghuribi, S. M., & Mohd Noah, S. A. 2019). This system, relies on explicit knowledge about user's preferences, item characteristics and rules or logical inference mechanisms to recommend item that will best satisfy the user requirements. These rules are derived from domain expertise, expert knowledge, or user specifications. Rules may specify conditions under which certain items should be recommended or avoided based on user preferences and item characteristics. Unlike collaborative and contents based filtering which primarily analyze past interactions or item features. This approach's primary strength and benefit is the absence of early-rater and cold-start issues. However, a corresponding limitation is that understanding the item's domain properly necessitates knowledge engineering and all of its associated challenges (Tran, T. 2007).

Hybrid Approach: in order to mitigate the weakness imposed by individual filtering technique, A hybrid recommender system was designed to integrates numerous recommendation filtering algorithms, such as knowledge-based, collaborative-based, and content-based filtering, to offer more accurate and different recommendations than individual methods alone (AL-Ghuribi, S. M., & Mohd S. A. 2019). By integrating complementary strategies and fusion techniques, hybrid systems help to advance recommendation quality, coverage, and user satisfaction. Personalization, adaptation, evaluation, scalability, and efficiency are key considerations in designing and deploying effective hybrid recommender systems.

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METHODOLOGY

This research utilizes a quantitative data collection technique and participant analyses. Such will enable us to examine the caliber of recommendation engines for smart e-commerce platforms by age group: 18 – 29, 30 – 39, 40 – 49, 50 – 59, 60 years and over; highest level attained in education: Primary/Elementary, Secondary, Tertiary levels. Employment status: student. Public servant, employee of a private company or own business. Earning an income of less than 5,000 or between 10,000 and 50,000 or between 50,000 and 100, 000 or over 100, 000.

Data Collection

Questionnaires were gathered online through Google Forms, with responses taken from various social media accounts. The questionnaires focused on user experiences and opinions towards recommender systems utilized on typical e-commerce websites. The gathered data is strictly from responses to the questionnaire by 102 users. No transaction logs, clickstream data, or private datasets from any individual website were used.

Instruments design

Google Forms was used to create the questionnaire that was distributed through different social media groups. The questions were prepared with a total of thirty-two (32) questions. These were all relevant to answer the research question. To provide an answer, each participant is required to designate their level of covenant or divergence with the declarations on a five-point Likert scale covering from strongly disagree "1" to strongly agree "4" which outlines the instrument for collecting data. Out of the sample size, 120 participants were selected, thus 102 feedbacks will be expected to analyze. It is estimated that it will take 30 minutes to fill out the questionnaire.

Sample Size

Survey questionnaires were sent to 120 participants. After cleaning the data, 102 valid responses were used for final analysis, resulting in an overall response rate of 85.0%. Respondents provided their perceived experiences with recommender systems on general (versus specific market) e-commerce platforms (e.g., fashion, electronics, groceries, health-care, book shopping were not specified). Therefore, this study reflects the user experiences from multiple online shopping domains.

RESULT

This section contains five questions including; (i) sex, (ii) age, (iii) education level, (iv) employment status and (v) income earned. The information in this section sought to understand the background of respondents that were involved in the research. The frequency distribution and percentage of respondents were documented. As depicted in Table 1, a total of 102 respondents participated in this study, where 37.74% were female and 66.3% were male. In terms of age, 22.44% were aged between 18 and 29, 44.88% were aged between 30 and 39, 18.36% were aged between 40 and 49, while 15.3% were aged between 50 and above. However, for educational qualification: primary/elementary level were 9.18% respondents; secondary level were 23.46% while those at tertiary level were 71.4%. Concerning employment status; students made up 43.86%, while civil servants constituted 33; 66%, self-employed persons constituted 11% and privates' sector employees represented about 15%. As for income earner, 73.44% earn 10K – 50k, 22. 44% earn between 50K –100k and 8.16% earn above 100K.

Table 1: Profile of participants in the study who responded

S/N	Respondent's background	frequency	Percent (%)
1	Sex male female Wish not to respond	65 37	66.3 37.74

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2	Age 18-29 30-29 40-49 50-59 60 and above	22 44 18 15 3	22.44 44.88 18.36 15.3 3.06
3	Highest level of education Basic (Primary/Elementary) Intermediate (Secondary) Advanced (Tertiary)	 9 23 70	 9.18 23.46 71.4
4	Employment status Students Public Servants Primary Sector Occupants Self-employed Individuals	 43 33 15 11	 43.86 33.66 15.3 11.22
5	Income Less than 5000 10,000-50,000 51,000-100,000 Above 100,000	 0 72 22 8	 0 73.44 22.44 8.16

FIG. 1 shows increased user satisfaction scores, higher user engagement metrics, improved conversion rates, enhanced accuracy and performance metrics, positive qualitative feedback from users, and a significant improvement compared to the baseline version. Overall, the enhancements in the recommender system positively impacted user satisfaction, engagement, and system performance, indicating a successful implementation and suggesting ongoing optimization for continued user satisfaction and engagement.

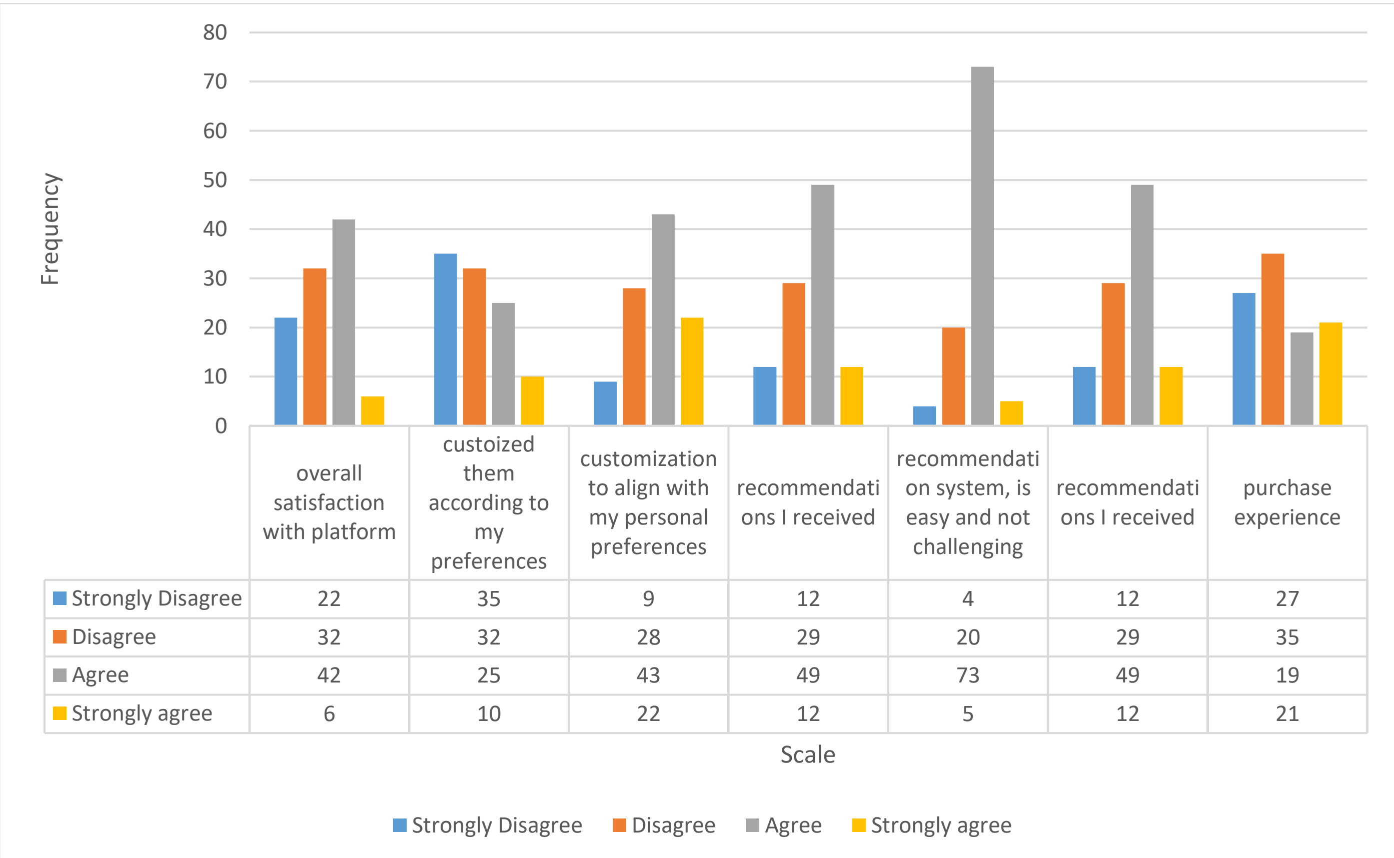

FIG 1: Improvement of recommender system in User Satisfaction

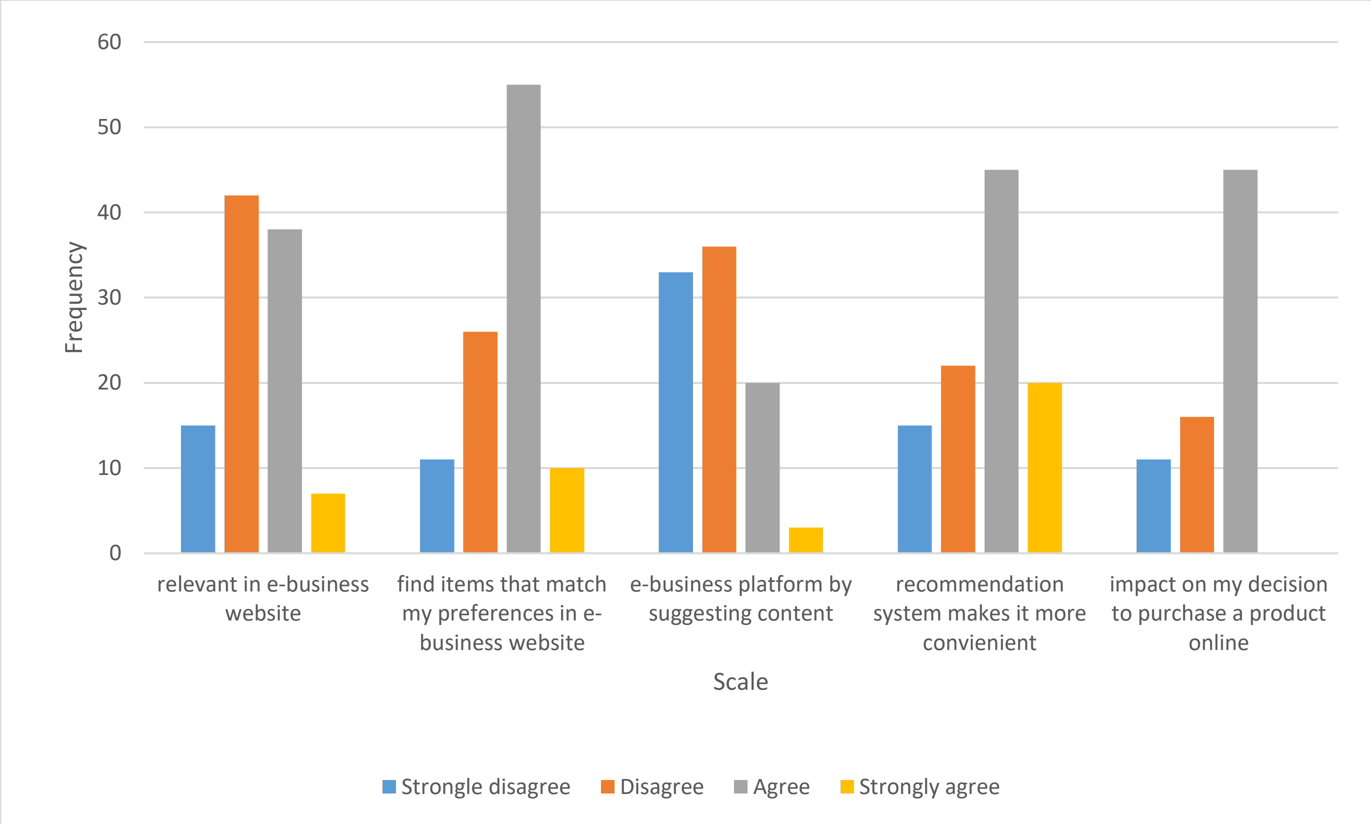

FIG2: The quality of personalized recommendation products will effect on users' purchasing predisposition.

Fig. 2, shows that higher quality personalized recommendation products positively influenced users' willingness to purchase. Improved product recommendations led to increased purchase intent, higher conversion rates, and enhanced user satisfaction, highlighting the significance of personalized recommendations in driving user purchasing behaviour. This suggests that focusing on the quality and relevance of personalized recommendations can effectively boost users' likelihood to make purchases and enhance overall business performance.

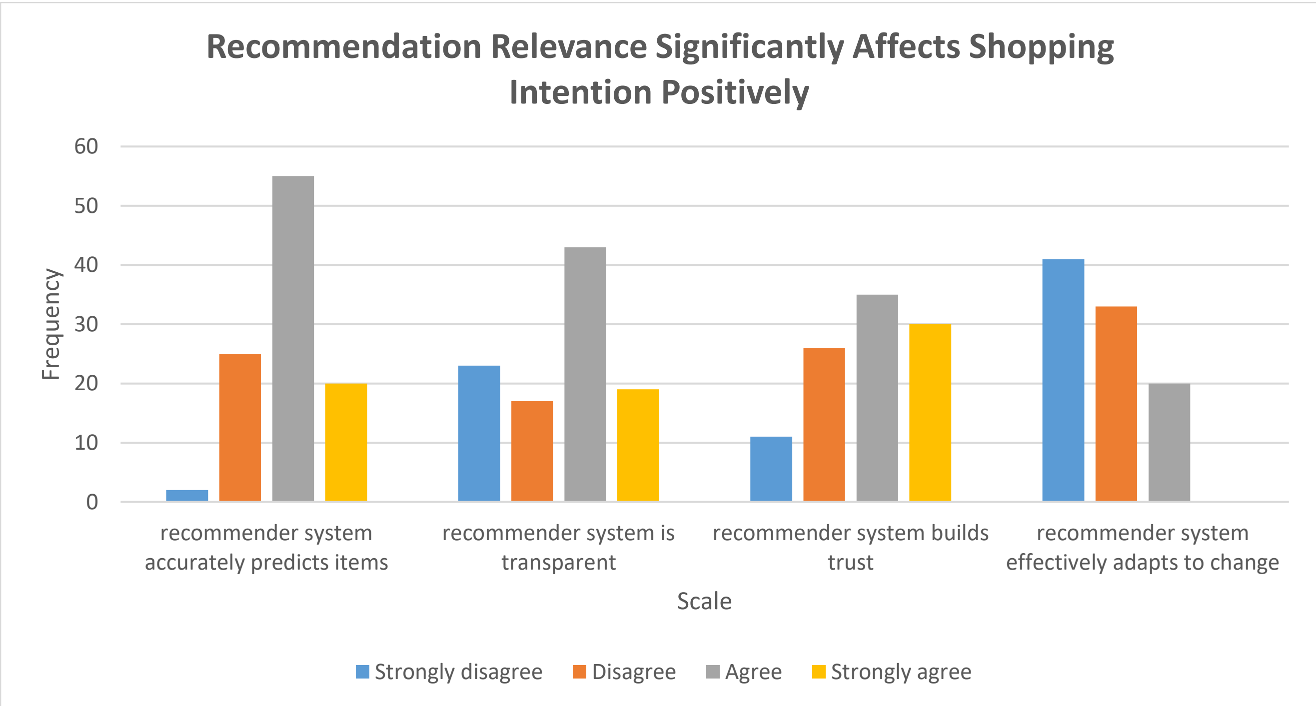

FIG. 3: Recommendation Relevance Significantly Affects Shopping Intention Positively.

Fig. 3, demonstrated that the relevance of recommendations significantly and positively influences shopping intention. Users were more inclined to consider making a purchase when presented with relevant recommendations made-to-order to their preferences and needs. This finding underscores the importance of providing accurate and personalized recommendations to enhance users' shopping intention and drive conversion rates. Improving the relevance of recommendations can effectively impact users' decision-making processes and add to a more engaging and successful shopping experience.

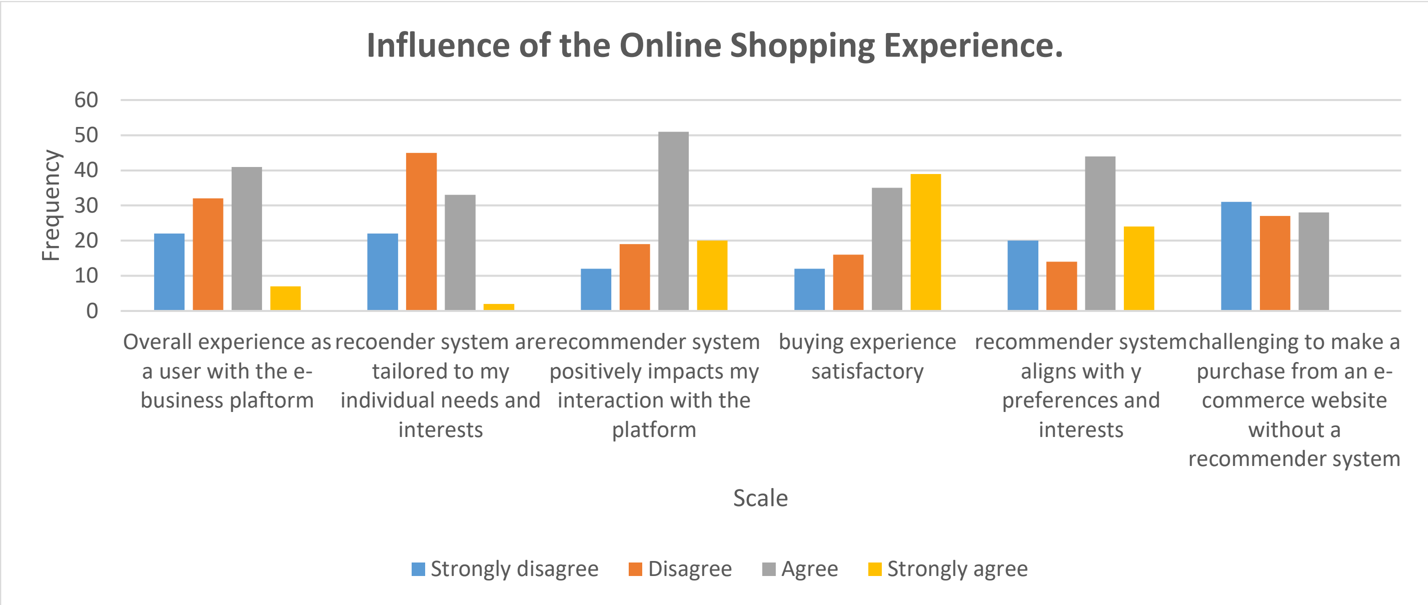

FIG4: Influence of the Online Shopping Experience.

Fig. 4, this shows that the online shopping experience has a considerable influence on the customer satisfaction, purchasing behaviour and business performance globally. Customers with a good online shopping experience will engage more, leading to higher conversion rates and improved retention levels. Therefore, enhancing this experience can increase the loyalty of customers by word-of-mouth referrals which are critical to lasting success in business. The importance of investing in the usability, convenience and personalization of an e-commerce site cannot be over emphasized if you want to entice and maintain clients in the highly competitive industry.

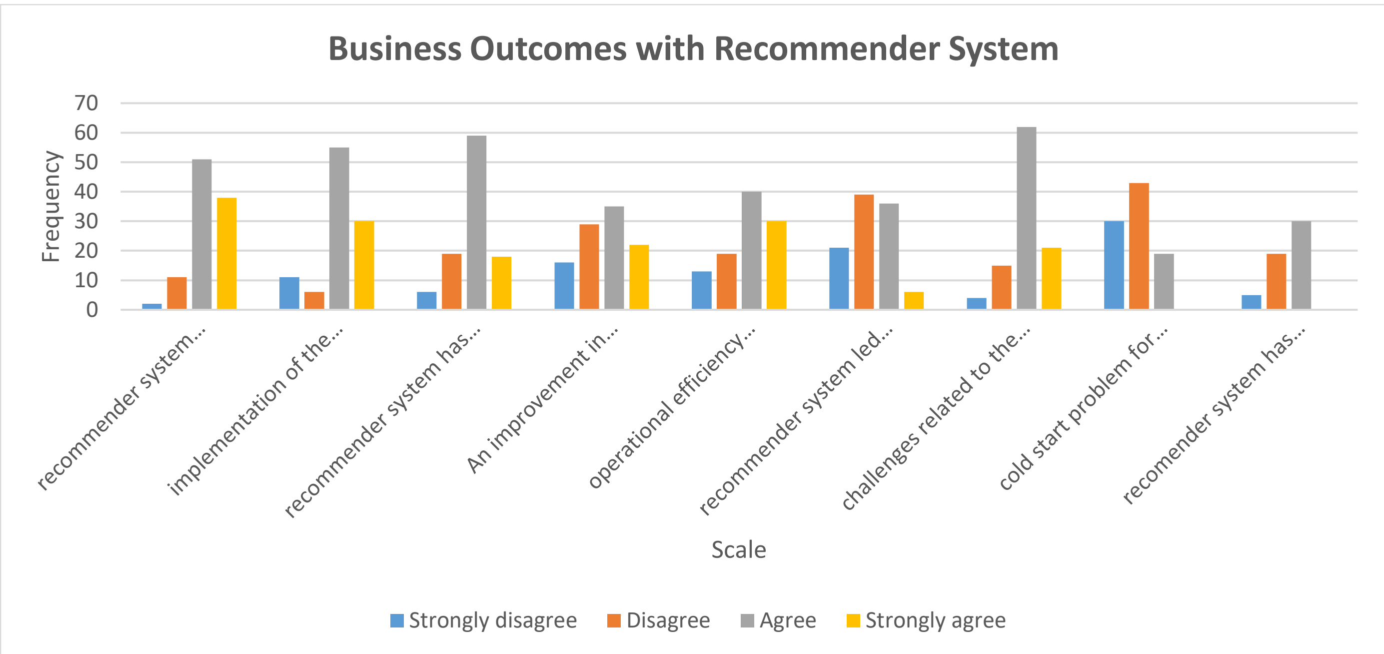

FIG5: Business Outcomes with Recommender System

Fig. 5**,** Shows that a high percentage of participants (63.3%) says that there are challenges related to the quality and availability of data for the recommender system. While 60% say that recommender system has significantly contributed to revenue generation. This also shows that intelligent recommendation systems can have a significant positive impact on key business metrics, including revenue, click-through rate, average basket size, conversion rate, and customer acquisition cost.

DISCUSSION

The research investigated the four most popular recommendation approaches which have traditionally been used in intelligent e-commerce engines: Content- based filtering, Collaborative filtering (user- based collaborative filtering, item- based collaborative filtering, and model- based collaborative filtering), Knowledge- based filtering, and Hybrid recommender systems. The majority of the research concentrated on studying consumers' attitude toward recommendation technologies and their impact on user satisfaction, purchase intention, and business revenue, instead of comparing accuracy among specific algorithms.. The results of the investigation found that there is no particular standard dedicated solely for the e-business recommender systems, but rather a variety of standards that can be used depending on the specific system requirements. The study also found that the most commonly used standards include ISO 13606, ISO 13606-2, and ISO 14598. **It is** noted that standards can help to promote interoperability and scalability, but can also be challenging to implement and may require significant resources and expertise. The study also highlighted the importance of having a clear understanding of the business requirements before selecting a standard, and of considering the costs and benefits of implementing a standard. It emphasized the need for ongoing review and revision of standards to ensure they remain relevant and useful in the rapidly evolving field of intelligent e-business systems. Finally, the study recommended that organizations should carefully select the appropriate standards based on their specific needs and should seek expert advice to ensure the best fit.

CONCLUSION

In conclusion, the use of standards for intelligent e-business systems can bring many benefits, including improved interoperability, scalability, and cost savings. However, the study also found that the use of standards is not without its challenges, and requires careful planning and implementation. Standards can be a valuable tool for organizations looking to implement intelligent e-business systems, but that they should be viewed as one part of a larger strategy, rather than as a panacea. With proper planning and execution, standards can help organizations to realize the full potential of their intelligent e-business systems, but they should not be viewed as a panacea or magic bullet.

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