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FACTORS INFLUENCING RECOMMENDER SYSTEM EFFECTIVITY ON CONTINUANCE USAGE INTENTION IN INDONESIAN E-COMMERCE USER

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ABSTRACT

As global market demand grows, e-commerce platforms face an increasingly competitive environment and an ever-rising deluge of data. To sustain their operations and improve customer experience, several of these platforms have incorporated services to assist customers in sifting through mounds of information. One of these services is Recommendation System (RS), an algorithm designed to offer personalized suggestions tailored to a consumer's preference. The study intends to explore which RS factor which has the most influence on its performance and effectivity in the Indonesian e-commerce environment, one of the biggest e-commerce economies in the region. The RS factors analyzed includes: Diversity of Suggestions, Suggestion Accuracy, Suggestion Novelty, and Recommendation Quality, alongside sociological factors such as Usage Attitude, Familiarity, Trust, and Satisfaction. This study uses a modified Technology Acceptance Model (TAM) model to study the correlations between these factors, customer usage attitude, and their subsequent Continuance Usage Intention. The data is collected through questionnaires distributed to a minimum of 106 Jakarta residents, given the region's high concentration of e-commerce users. Results show that RS quality is driven by Accuracy, Novelty, and Diversity, with Accuracy yielding the highest influence. Higher RS quality then positively affect both the user's Usage Attitude and Trust, while Usage Attitude boosts User Satisfaction, all of which increases the user's continued usage intention. However, Perceived Usefulness yields a stronger impact on Usage Attitude than Recommendation Quality and Perceived Ease of Use, indicating that the system's practical utility yields more impact on user perception than usability or technical quality.
Future RS development should focus on increasing long-term use by improving customer satisfaction through increased system usability and RS accuracy, supported to a lesser extent by features that bolster user trust and familiarity. These findings offer insight on optimizing RS designs and fostering continued engagement in Indonesia's e-commerce landscape.

Keywords: *Artificial Intelligence, Recommendation System, E-Commerce, Customer Continuance Usage Intention, Recommendation Quality.*

1. INTRODUCTION

In our technology-driven world, e-Commerce has become an increasingly important cornerstone of our daily shopping. This is especially prominent in highly-populated and internet-savvy nations like Indonesia, whose population have begun to increasingly rely on e-commerce networks for routine transactions. This user boom is showcased in the rising value of Indonesia's retail e-commerce sales, which reached up to 37.4 billion US dollars in 2022 and is projected to rise to roughly 90.47 billion US dollars by 2026 [1]. This surge has also impacted the market on a global scale, allowing the segment to reap 5.8 trillion dollars in total sales with a projected growth rate of 39%. It's more than likely that this growth will continue to increase exponentially with current trends, with one valuation stating that the industry will leap past 8 trillion dollars by the end of 2026 [2].

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As a result of its rapid growth in both market scope and user number, e-commerce platforms are faced with an emergent issue: data overload. The increased number of merchants and customers demands means that e-commerce marketplaces have to store and manage more and more customer information and item data. As a result, e-marketplace product libraries have turned into an extensive buildup of data that, for most users, could be overwhelming. This data buildup may prevent users from effectively browsing through the collection, stopping them from finding potentially useful and important items or making informed purchase decisions. RS are a type of automated sorting algorithms commonly employed to assist the users in recognizing correct or relevant info from a pool of options or data sets [3].E-commerce employs it to mitigate the problem of information overload by having the RS go through the website's item database and provide the visitor with the filtered list of products which corresponds with their customer behavior, their search history and purchasing history (2024).

As a result of its usefulness in the age of rapid e-commerce growth and smart devices, RS has become one of the most common and critical components of online marketplaces [4]. In 2021 alone, the global market for recommendation systems was valued at 2.69 billion dollars, with expectations to grow to 15.10 billion dollars by 2026, reflecting a compound annual growth rate (CAGR) of 37.79% from 2022 to 2026 [5]. It's even stated that by at least the year 2030, roughly 70% of companies will use AI to enhance their customer experience in a manner similar to e-commerce[6]. Major companies such as Amazon and eBay have also pioneered these automated recommendation systems due to the scale of their operations, with such systems accounting for 35% of Amazon's online sales [7] .

Due to its relevance within the already hypercompetitive world of e-commerce, the technology remains under a constant state of research and development. Various experts from academical fields such as business, marketing, data mining, forecasting security, and artificial intelligence (AI) have improved the system's performance and applicability in various ways [8]. To maintain competitiveness in the global marketplace, Indonesia must also prioritize the advancement of the recommendation systems employed by its leading e-commerce platforms. Given e-commerce's significant contribution to Indonesia's economic growth, falling behind in this area could have serious financial repercussions for the country. The need to improve the current system becomes more urgent as Indonesia's e-commerce business continues to expand exponentially. Such developments have enormous potential advantages, but there are also considerable risks involved in delay or insufficient advancement. To strengthen this market, it is crucial to push for the development of new approaches and focused algorithms that enable recommendation systems (RS) to meet their required level of effectiveness. To continue to be effective, newer RS models need to have a thorough grasp on its customers, be adaptable to new data, and undergo continuous evaluations to ensure their algorithm remains accurate and relevant despite changing customer trends [9].

Thus, the study aims to contribute to this effort by looking into the inner workings of the system, identifying the primary variables that influence its performance and quality, and determining which factors should be the primary focus of future research. However, while there is a number of research covering the more mechanical factors behind the RS's quality (ie. Recommendation Accuracy, Variety, and Uniqueness), there remains a gap regarding the more user-side aspects (ie. Usage Attitude, Trust). Hence, the current study wishes to investigate a model which includes these less-explored factors and uncover a full picture of the determinants and elements that shape an RS's quality. Futhermore, a prior study has posited that an user's long term engagement is positively correlated with an user's satisfaction and trust [10]. However, this outcome has not been tested with the prior frame in mind, and as such their correlative effect with TAM factors is currently unexplored. In addition, While a considerable amount of studies exists on the effectiveness of RS in driving up customer purchase intention, most research in this field primarily focuses on the system's ability to influence initial Purchase Intention. However, less attention has been commited to the RS's effectiveness in inducing long-term engagement or Continuous Usage Intention. This is particularly critical, as a key goal in e-commerce involves generating not just immediate purchases, but also in ensuring that the system remains utilized by customers through long term engagement. Furthermore, limited attention has been given to the potential role of TAM factor as a mediator between RS effectiveness and usage behaviour, despite the model's prominent influence in determining future usage.

The objective of this study is to address these research gaps by focusing on a distinct area compared to prior research. This includes examining the factors that are important in developing recommendation systems that not only provide options, but also encourage continued usage over time. This approach is supported by the understanding that creating systems designed for sustained use is significantly more advantageous than merely providing options without fostering regular engagement in e-commerce contexts. Additionally, this study explores several factors related to RS quality, incorporating the TAM framework to investigate whether a system perceived as useful and easy to use can influence customers' opinion of the system, as well as its effects ability to foster repeated use. Furthermore, the study examines whether customers' knowledge of the products recommended by the system can strengthen their trust in the system, ultimately contributing to their sustained use of it during e-commerce shopping experiences. The study will also include Usage Attitude as a key component of the TAM framework, which posits that the perceived ease of use and usefulness of a system can influence an individual's attitude regarding system usage. Prior studies have used TAM in their model as a way to measure e-commerce use [11], but Usage Attitude was overlooked in favor of Perceived Usefulness and Ease of Use. As per a previous study, it is also considered that the satisfaction and trust felt by the user a critical factor in establishing a relationship with continuance usage intention [10]. The study also seeks to determine whether the Usage Attitude significantly impact their user's satisfaction, thereby encouraging sustained interest and engagement with the system.

In addition, most models proposed by previous studies were tested with initial purchases or Purchase Intention in mind [11]. However, Continuance Intention has been identified as a more critical component of an organization or internet service's sustainability than initial adoption [12]. This is because Continuance Intention signifies repeated consumer use and loyalty, while Purchase Intention merely indicates a one-time transaction without guaranteeing future interactions or long-term commitment. It's also postulated that attracting new customers can cost five times more than retaining an existing consumer base. Hence, the study aims to extend previous frameworks by focusing on Continuance Intention as its end goal.

Based on the problem detailed above, this research seeks to identify and answer several problems regarding the factors influencing recommender effectivity on Continuance Usage Intention in Indonesian E-Commerce User. The questions we seek to explore about this topic can be summed up in the following list:

1. What is the public's reception to the current recommendation systems?
2. What are the factors that play an important role in the system's effectiveness?
3. How does technological adoption (TAM) factors and Recommendation Quality affect a consumer's Usage Attitude in the context of e-commerce?
4. How does user Satisfaction and Trust affect Continuance Intention within the framework of technological e-commerce adoption?

2. THEORETICAL BACKGROUND

2.1. E-Commerce Definition

Electronic Commerce or E-Commerce is defined as actions or activities surrounding the act of purchasing, offering, and trading products and services through electronic mediums such as the internet [13]. These activities may include electronic payments, online shopping, online banking, and online auctions. Furthermore, these transactions are typically conducted with the help of modern technology such as the internet marketplaces, electronic data interchange (EDI), and electronic record keeping. Subsequently, these technologies are also employed to manage its other activities, including electronic product exchanges, swift digital content and asset supply, direct marketing, and post-purchase servicing. Owing to the significant surge in technological adoption, E-Commerce has emerged as one of the fastest growing sectors in the globe. In the year 2021, the e-retail industry alone secured an estimated $4.2 trillion profit. This value is estimated to ramp up to $5.42 trillion in 2022 and $6.38 trillion by 2024 [14]. As was previously noted, e-commerce is a digitally based industry that benefits immensely from technological advancements, such as artificial intelligence and other forms of automation like recommendation models.

2.2. Recommendation Systems

Recommendation Systems (RS) are automated filtering systems intended to suggest goods or products that are pertinent to consumers in order to increase sales [15]. These systems were first introduced as a collaborative filtering network, which filtered email documents according to audiences. es. This process involved analyzing elements within documents, such as messages, replies, and annotations, allowing the system to effectively identify and select relevant data, often surpassing the capabilities of similar programs. With the rapid expansion of the internet and the growth of e-commerce, it has become increasingly difficult for customers to find suitable items amidst a vast array of products. Recommender systems have been suggested in earlier IS research literature as a workable way for online retailers to address these data sparsity and scalability issues and offer customized item recommendations that change the purchasing habits of customers[16], [17], [18]. These systems are crucial to decision-making because they help customers minimize risks [19] and maximize profits [20] by improving sales efficiency, which benefits both online retailers and consumers.This challenge can negatively impact user interest and reduce sales. Consequently, recommendation systems are now widely implemented in e-commerce to quickly and efficiently scan databases and generate recommendations based on factors such as user demographics, item attributes, and user preferences [21]. This enables customers to browse items without sifting through the entire product catalog.

Typically, a recommendation system will require three basic components in order to function : a large collection of information which contains all data the recommender system needs to function (dataset), the formula which is used to analyze through and select relevant data and pattern from the dataset (algorithm), and an interface which bridges the recommendation and the user by presenting and displaying the items chosen by the algorithm directly into their feed through seamlessly integrated menus, notifications, and communication channels (output interference) [22].

A recommendation system then uses these components to run its three phases: Modeling, Prediction, and Recommendation. In the Modeling Phase, a data model is created comprising user profiles, item profiles, and a rating matrix, which records user preferences for items and their features [22]. The Prediction Phase then uses this model to predict the ratings users would assign to items they haven't yet encountered by comparing item features to the features of previously rated items. Finally, the Recommendation Phase will rank these items based on their predicted ratings and assemble a list of highest-rated items to be presented to the user. The recommendation process also involves steps like data collection, preprocessing, algorithmic analysis, and recommendation ranking. There are several types of algorithmic analysis an RS may use, with the most commonly used method being a hybridized mixture of Content-Based Filtering (based on item similarity) and Collaborative Filtering (based on similar user preferences) [23].

2.3. E-Commerce and RS in Indonesia

With roughly 58.63 million e-commerce users in its population [24], Indonesia stands as one of the largest and fastest growing e-commerce markets in the world. As more and more of its population begins to rely on e-commerce, it's little wonder that an increasing number of businesses within the nation have chosen to establish secondary stores on e-commerce platforms as well, further driving e-commerce expansion. In order to test the inner workings of an RS within Indonesia's environment, the research aims to use two of Indonesia's largest and most relevant e-commerce platforms as a representative of its present market conditions. The two include : Shopee (currently stands as the biggest and most well-known marketplace in Indonesia, with 227.6 million visits each month and 7.7 million downloads) and Tokopedia, the second-largest marketplace in the country, follows suit with 95.7 million monthly visits and 2.4 million mobile downloads [25]. Shopee is a highly influential e-commerce platform with significant sales, reaching $18.6 billion in 2023 [26]. By early 2021, it had over 14 million merchants and processed nearly 1.1 billion items, with sales growing to over 2 billion items by the end of 2021 [27].Given the vast number of items and merchants, Shopee employs a recommendation system to help users navigate and make informed purchasing decisions. Thus, like major e-commerce marketplace platforms such as Amazon and eBay, Shopee employs a recommendation system to help users efficiently and accurately sort through their collective inventory. Thus, if one wishes to study the Indonesian e-commerce environment, the two e-commerce companies and their recommendation system would serve as an excellent representative environment.

Shopee's recommendation system consists of three intercrossed methods: popularity-based recommendations, content-based recommendations, and collaborative filtering [28].Popularity-based recommendations make suggestions for products based on how well-liked they are overall by users, working under the assumption that well-liked goods are more likely to be liked by a large number of people [29]. Conversely, content-based recommendations compare word, image, and user rating similarities to suggest products based on a user's past interactions and profile information [30]. Meanwhile, collaborative filtering determines its recommendations by identifying users with shared traits (such as search history and geographic regions) and using their past activities and purchase history as a basis [31] .

In comparison, Tokopedia, one of Shopee's largest regional competitors, uses a combination of two methods in their recommendation system: session-based and ranking-based recommendations. Session-based recommendations work by taking in user session data, such as their browse history and recorded purchases, and suggest items based on similarity or proximity vectors to the sample data. On the other hand, ranking-based recommendations work by assembling a score map for user preferences based on past behavior and demographic data. This map will then be used to selectively filter through the e-commerce database and recommend items that fit the established criterion, ensuring that the user's recommendation is populated by items liked by a 'neighborhood' of similar users [32]. It must be noted that Shopee and Tokopedia both supplement their respective systems with a popularity-based recommendation system, which recommends items highly rated or frequently visited by their userbase, indicating a mutual attempt to appeal to their broader userbase through broader and universal recommendations.

2.4. TAM Model

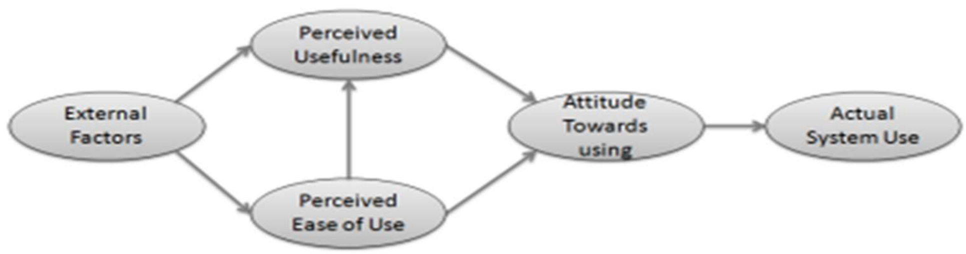

Figure 1: Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is a theoretical framework in the field of Information Systems to predict and explain the acceptance of the adoption of computing and information technology and the influence of new modifications on technology acceptance [33]. TAM was developed based on the Theory of Reasoned Action (TRA), with the assumption that behavior and attitudes towards a technology are the main factors influencing the adoption and use of technology, which then depend on the Perceived Ease of Use and Perceived Effectiveness of the system. Perceived Ease of Use is how users perceive the effort made by the technology. The higher the Perceived Ease of Use, the more users believe that the technology will reduce the effort needed by users to achieve a goal and the more they believe that the challenges in using it are smaller than the benefits provided by its use. Then, Perceived usefulness can occur when users feel the benefits of existing technology. The greater the benefits perceived, the more users believe that the technology will make it easier or provide tangential benefits for them. Then, this second factor influences the behavior and attitudes of users towards the technology on the involvement, adoption and actual use of the technology. Several studies have used the TAM framework and agreed that it is a reliable model to include technology adoption in the context of e-commerce and RS [34]. Therefore, this framework is considered appropriate to radiate the e-commerce and RS factors studied in the scope of the study.

2.5. RS Quality and It's Determining Factors

In order to improve the RS system's output, it is necessary to understand how the system benefits e-commerce and the factors that play a part in its operations. Previous studies have shown that one of the most important benefits provided by an RS is its positive influence on the consumer's continuance usage intention. An intention is defined as the likelihood of an individual to perform a specific behavior; the higher the intention, the more likely they are to do it [35]. Within the context of e-commerce, continuance usage intention reflects a customer's likelihood to continue using the website to browse or purchase products. The factor is especially important because these systems are designed to reduce information overload for consumers and make the website more tolerable

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while facilitating product discovery, thereby increasing the product's likelihood of purchase and the store's visitation rates [36]. Studies have shown that well-designed recommendation systems can significantly boost purchase intention by presenting consumers with options that are more relevant to their needs, leading to higher conversion rates and a higher degree of customer retention [37].

RS also provides prominent landing page space to a selected set of recommended products, which serve as decentralized signals of quality and potential demand, further incentivizing them to continue browsing and increase their Continuance Intention. We intend to discover the factors within RS that play the most prominent role in boosting the customer's continuance usage intention. While there has been prior studies regarding the RS factors with the most prominent effect on the customer's intention to purchase, a vast majority of them is focused on the customer's immediate purchase draw and mainly focus on the Recommendation System Quality, as determined by factors such as Perceived Accuracy, Novelty, and Diversity [34], [38]. Meanwhile, there is still a shortage of work focused on Continuance Usage Intention as not just an indicator of a customer's likelihood to purchase something, but also their chance to revisit and use the site even after initial contact.

Some external variables and factors that have a logical relationship with TAM components and CUI were identified in the research. Despite this, there is still a noticeable gap in research regarding the full impact of recommendation systems on an e-commerce platform's ability to gauge and influence a customer's CUI. Additionally, the correlation between these systems and the factors affecting them remains underexplored. Addressing these gaps is essential for identifying the factors that most significantly influence e-commerce sales and the efficiency of recommendation systems. In this research, the Technology Acceptance Model (TAM) will be employed to assess the determinants of e-commerce CUI, as well as to identify which aspects are most affected by the quality of the recommendation system. The following factors and aspects will serve as the basis for the research model variables.

2.5.1. Diversity of suggestions

In this study, Diversity of Suggestion (DS) is the degree of variation in the system's recommendation outcomes and is intended to provide users with new and diverse options that they have not seen before [39]. This factor was selected because the increase in number of recommendations is beneficial for continuance usage intention of consumers, especially if these recommendations are personalized.

2.5.2. Suggestion accuracy

Suggestion Accuracy (SA) is the degree to which a system's product recommendations match consumers' pre-existing preferences before engaging in search activities [40] SA is achieved by proposing products based on user search behaviors. Higher levels of SA, which indicate greater congruence with individual consumer preferences, are thought to boost customers' willingness to purchase.

2.5.3. Suggestion novelty

Suggestion Novelty (SN) refers to the extent to which the recommendation system introduces customers to products they have not previously used or interacted with[11] . It is proposed that the novelty and distinctiveness of these items influence the perceived value of the recommendation system, as one of its key objectives is to present new products that may capture consumer interest and spark curiosity.

2.5.4. Recommendation quality

Recommendation Quality (RQ) is a measure of the capability of the system in fulfilling the role it has been assigned to perform by the users. This quality is typically measured by determining if the recommendation system's mechanism has improved the customer's shopping experience in an efficient and personalized manner. RQ is considered a critical factor in the overall performance of an RS. Data obtained from prior studies even indicate that about one-third (35%) of the total revenue of Amazon can be effectively traced to the quality of the company's recommendation system [41]. Thus, RQ will act as a reflective indicator of the RS's perceived performance and will be used to monitor the influence of other factors. Previous primary sources have primarily focused in examining and confirming the role of RS Quality in influencing Purchase Intention through psychological factors, namely Satisfaction. In contrast, this study aims to examine RS Quality and its influence under a differing lens, namely through its ability to foster continuance usage intention through the mediation of more psychological factors in the form of Usage Attitude, Trust, and User Satisfaction.

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2.5.5. Perceived ease of use

Perceived Ease of Use (EU) is the degree of convenience which the users feel while using the system, and the ease with which they can obtain information because of the recommendations. This covers the ease and convenience with which the customer navigates the system. This factor has been noted to impact the quality of the RS, which in turn impacts the user's attitude to the system [42].It is postulated that a system that is simpler to use will result in increased satisfaction on the part of the users, longer usage and, therefore, greater chance of transactions.

2.5.6. Perceived usefulness

Perceived Usefulness (PU) is a measurement of the extent in which recommendation systems help customers make shopping easier for them [43].Because it increases the user's utility of the platform, it is hypothesized that a RS's utility possesses a major impact on the platform's success. This is seen as crucial and is used to gauge how much the system's general usefulness has impacted its overall quality.

2.5.7. Usage attitude

Usage Attitude (UA) refers to the user's overall approach or emotional disposition regarding the use of a new technology, such as the RS within the context of this study, be it positive or negative [44]. Taking into account the results of a previous study in the same area, it can be stated that the user's acceptance of the system is determined by the perceived usefulness and ease of use of the system [45]. Another factor which affects it is the quality of the RS itself, which directly influences the RS's perceived usefulness and ease of use and thus the user's attitude towards its use [11] .

2.5.8. Satisfaction

Satisfaction (SA) refers to the degree of fulfillment and satisfaction the customer feels about the system's provided services [46]. Previous research has shown this satisfaction is massively influenced by the ease and convenience of online shopping (PEU, PU), which in turn possesses a significant effect on the customer's behavioral intentions [47]. Furthermore, while research on recommender systems often prioritizes enhancing model performance, US has been noted to be an equally crucial factor in guaranteeing the success of an e-commerce. A previous study has explored the relationship between system performance and user satisfaction and have found them to be directly and positively cor relative [48].Thus, it is determined that the RS's US will be regarded as a decisive factor in determining the attitude and behavior (UA) of a customer, as affected by the RQ.

2.5.9. Familiarity

Familiarity (FA) in this research refers to the extent to which the recommended product list consists of items that already enjoy a certain level of popularity among other consumers, aiming to attract customer interest in these recommended products [49].It is suggested that familiarity, similar to variety, may play a role in stimulating customer interest [11].

2.5.10. Trust

Trust (TR) is the degree of trust the user has in RS to perform its tasks correctly, as well as their trust in the RS's product recommendation. As noted by a preceding study, a customer's level of trust in the things that are recommended to them depends on how familiar the results of the advice are to them. Customers have been noted to be more confident in their purchases when the things offered are similar to those they have previously engaged with [50]. Nevertheless, the association between a number of the recommendation system's components as well as other potential process-influencing elements, have not been thoroughly investigated in the aforementioned studies.

2.5.11. Continuance usage intention

Continuance Usage Intention (CU) in the context of Indonesian e-commerce refers to a user's intention to keep using an e-commerce platform or its features, such as recommendation systems, after their initial adoption or first impression. [51] .For e-commerce businesses, a sustainable supply of customers with a strong desire to continue using the product is essential since it has a direct impact on customer lifetime value, recurring business, and customer loyalty [52]. In the modern e-retail world, continual usage intention and the devoted customer base that comes with it becomes increasingly more crucial as the online platforms begin to face deadlocks from other e-commerce platforms and ever-increasing competition from all sides, not dissimilar to other online-bsed industries [53]. Recommendations that are in line with the preferences of the consumer boost platform trust, which in turn leads to enhanced customer satisfaction and the chance that the service will be used again. Recent studies have also expanded on these findings, highlighting the role of personalized recommendations in boosting customer satisfaction and, in turn, continuance usage intention

3. METHODOLOGY

3.1. Research Model and Hypothesis

In order to create a more in-depth model of the RS's factors and their correlative effects towards consumer continuance usage intention, the study will utilize the previously discussed TAM model as it's basis. The model is chosen because of its proficiency and accuracy in predicting consumer behavior and technological adoption, both of which covers the topic of this study. The study proposes that the consumer's UA is directly affected by a combination of an RS's three factors : RQ (and its subsequent parts, such as DS, SA, and SN), PEU, and PU. The UA felt by the consumers will then directly affect the user's US with the RS. The consumer's collective US, along with TR (which is also influenced by FA), will then play a direct role in affecting the CUI. In accordance with the discussion above, the following hypothesis were proposed:

H1: *Diversity of Suggestion* significantly affects *Recommendation Quality.*

In this hypothesis, the investigation aims to determine whether the *Diversity of Suggestion* impacts *Recommendation Quality* (RQ) within Indonesia's e-commerce environment. It is posited that varied or diverse recommended products given by RS to users can increase the quality of the recommendation itself. This assumption is based on the results of a previous study, which shows that recommendation diversity or variety of the recommendation can affect the quality of recommendation. The study posits that this is because a more diverse list of recommended products will prevent the selection from becoming monotonous, thus giving users a higher selection of options and increasing their satisfaction, as well as the overall quality of recommendation increase [38].

H2: *Suggestion Accuracy* significantly and positively affects *Recommendation Quality*.

This hypothesis proposes that there is a strong correlation between *Suggestion accuracy* and *Recommendation Quality* (RQ) within Indonesia's e-commerce environment. The proposition is supported by earlier works, which indicated that the Accuracy of a user's preferences positively impacts RQ. Previous research has also noted that when RS provides recommendations that match user preferences, users are more likely to give a positive response to the system because the recommendations given are appropriate, thus improving the perceived quality of the RS [38].

H3: *Suggestion Novelty* significantly and positively affects *Recommendation Quality.*

This hypothesis posits that there is a direct correlation between the uniqueness of an RS's recommendation selection and RQ within Indonesia's e-commerce environment. Based on existing studies, it has previously been observed that uniqueness has a positive impact on RQ, and that new or fresh products can increase the quality of recommendation itself. The cause of this is posited to be the interest created when users are offered novel items, they are unfamiliar with, which in turn helps make the recommendation more enticing and effective [38].

H4: *Recommendation Quality* significantly and positively affects *Usage Attitude.*

It is proposed that *Recommendation Quality* (RQ) significantly influences users' *Usage Attitude* (UA) toward the RS within Indonesia's e-commerce environment. The proposition is supported by earlier works that a higher-quality recommendation system aligns more effectively with user preferences, leading to a more positive perception of the system [11].

H5: *Recommendation Quality* significantly and positively affects *Trust.*

This hypothesis postulates that RQ results in a positive effect on *Trust* (TR) in the context of e-commerce in Indonesia. Prior Works found that RQ does have an impact on Trust as a better quality of RS can give the user more accurate and engaging recommendations which in turn enhances their trust in the system [54].

H6: *Perceived Ease of Use* significantly and positively affects *Usage Attitude.*

This hypothesis postulates that EU has a direct effect on UA in Indonesia's e-commerce context. Prior research has shown that EU has a significant effect on UA as navigability of the system is one of the factors that make the user experience better and leaves a positive impression about the system.[45].

H7: *Perceived Ease of Use* significantly and positively affects *Perceived Usefulness.*

The hypothesis forwards the notion that a user's EU possesses a substantial effect towards PU within Indonesia's e-commerce environment. According to previous studies, the two have been noted to be positively correlated. It is assumed, based on prior data, that this is because the easier a system is to use and navigate through, the quicker the user can use it and thus the more useful the system is [34].

H8: *Perceived Usefulness* significantly and positively affects *Usage Attitude.*

In this hypothesis, it is posited that there exists a direct and positive correlation effect towards UA within Indonesia's e-commerce environment. As explained by previous studies, PU has been observed to directly impact a user's UA. The research hypothesis that the usefulness of a system can help bring positive attitude from users towards the system through the utility it provides [55].

H9: *Usage Attitude* significantly and positively affects *Satisfaction.*

The following hypothesis proposes that there exists a positive and significant correlation between UA and US within the Indonesian e-commerce environment. As observed by preceding studies, it was noted that larger levels of approval and understanding that comes from higher high-quality recommendations result in a larger chance of engagement, enhancing user satisfaction [56].

H10: *Satisfaction* significantly and positively affects *Continuance Usage Intention.*

The hypothesis forwards the notion that Satisfaction possesses a positive effect on *Continuance Usage Intention* (CU) within Indonesia's e-commerce. This notion is backed by a previous study, which states that the satisfaction the consumer felt from the recommendation has a major and positive role towards the consumer's CU [57]. These associations can be attributed to the fact that the higher the amount of enjoyment the user feels as a consequence of the RS, the more likely they are to reuse the system or e-commerce in future endeavors. In summary, the higher performance a service or product was perceived, the more likely they'll be back [58].

H11: *Familiarity* significantly and positively affects *Trust.*

The hypothesis forwards the notion that a user's *Familiarity* with the recommended items has a direct impact towards a user's *Trust* within Indonesia's e-commerce environment. As seen in previous studies, the positive impact *Familiarity* has on *Trust* have been recorded within the e-commerce context before, validating it. Based on supporting data, it is proposed that this correlation occurs because when a user is familiar or familiar with an item, it gives the user a sense of certainty of sureness in the RS's choice, increasing the user's trust in the results of the RS [59].

H12: *Trust* significantly and positively affects *Continuance Usage Intention*.

The hypothesis, based on the backings of previous data, has reason to believe that a user's Trust in the RS directly influences a user's CU in a positive manner within Indonesia's e-commerce environment, especially in RS that is built or has social elements [46]. Similarly, previous works have shown that the Trust a customer places on an RS result or service possesses a similarly high influence on a customer's purchase intention within the context of e-commerce and e-payment [60]. It can thus be summarized that the more trust users have in a recommendation system, the more comfortable they are with using the system as intended. This would, in turn, increase the user's likelihood of making or hosting purchases through the system [61]. From the factors & hypotheses discussed above, the following research model can be assembed

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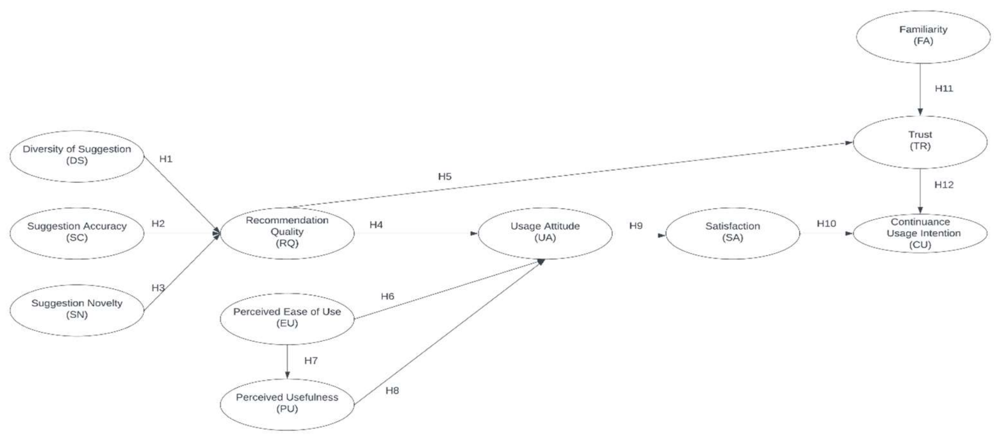

Figure 2: Research Model

3.2. Sample Collection Method

This data for study will be gathered from online questionnaires sent to an anonymous group and undergraduate and graduate students, who participated voluntarily in this study. The study's goal is to identify and locate a respondent who met the target criteria (e.g., young customers typically select e-commerce because they are accustomed to the procedures of online shopping). Therefore, our population will be compromised of the general e-commerce shoppers, with a focus on younger demographic groups and particularly on those who have previously joined or used e-commerce. The study will focus on Jakarta, which better represents our target market than most places because it has one of the country's largest population distributions of e-commerce consumers (estimated at 58% of the total population)[62]. The minimum sample required for this study was calculated using Slovin's formula, with an acceptable error margin of 10% and accuracy rate of 90%. The formula is as detailed below:

$$n = N/(1+N*e2)$$

Description:

n = the sample size
N = total population size
e = the margin of error (as a decimal)

Using this formulation, the minimum sample amount needed to represent Indonesia's 58.63 million e-commerce user population is:

n = 58,630,000 / (1 + 58.630.000 (0.10)2)
n = 58,630,000 / (1+ 58.630.000 (0.01))
n= 58.630.000 / 586.300
n = 100 minimum respondents

The study's questionnaire consists of five main sections : Biodata, Recommendation Quality, Usage Attitude, External Factors, Continuance Usage Intention. The questions and indicators in the questionnaires were derived from previous literature and studies. Each question acts as an indicator for a variable, and is measured based on a Likert Scale that ranges from one (extremely disagree) to five (extremely agree). The Likert Scale is judged as suitable for this research because of its compatibility with social studies [63]. To effectively reach the study's targeted Indonesian demographic, the questionnaire were translated into Bahasa Indonesia. Additionally, a brief notification was provided with the questionnaire to inform participants of the study's purpose encourage truthful answers. The test's general readability, reliability, and clarity were tested by a trial group. Their input was used to refine the questionnaire, and the finished product are as listed:

Table 1:Questionnaire Aspects & Indicator

Aspect	No.	Indicators	References
Diversity of Suggestion	DS1	The recommended items by the recommender system are diverse.	[11], [54]
	DS2	The items recommended to me are not similar	

		to each other.	
	DS3	The items recommended to me are assorted and varied.	
Suggestion Accuracy	SC1	The items recommended to me match my interests.	[11], [54]
	SC2	The recommender system gave me good advice.	
	SC3	I am interested in the items recommended to me.	
Suggestion Novelty	SN1	The items recommended to me are new and interesting.	[11], [54]
	SN2	This recommender system helped me find new items.	
	SN3	This recommender system recommends items to me that are beyond my expectations.	
Recommendation Quality	RQ1	Recommender system suggestions are helpful.	[11], [54]
	RQ2	Recommender system suggestions are particularly relevant.	
	RQ3	I like the items suggested by the e-commerce app.	
	RQ4	I feel that the Recommender System helps me decide what to buy.	
Perceived Ease of Use	PE1	I became familiar with the recommender system very quickly.	[38]
	PE2	The items recommended by the system were easy to find and interact with	
	PE3	I can easily find and view the recommended item list.	
Perceived Usefulness	PU1	The recommender helped me find the ideal products.	[11], [38]
	PU2	The recommender gave good suggestions.	
	PU3	I feel supported in selecting the items to buy with the help of the recommender.	
Usage Attitude	UA1	I will choose the features recommended, given the opportunity.	[38], [64]
	UA2	I'm positive about the e-commerce	

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		recommendation system.	
	UA3	I think that the e-commerce recommendation system is a valuable tool resource.	
Satisfaction	SA1	I'm generally satisfied with the content produced by the e-commerce recommendation.	[11], [64]
	SA2	I enjoy shopping from an e-commerce with the aid of the recommender system	
	SA3	This e-commerce recommendation system provided me a good shopping experience.	
	SA4	The contents recommended by the e-commerce recommender system can satisfy my needs and expectations.	
Familiarity	FA1	The e-commerce recommender system just provided me with the familiar products.	[11], [49]
	FA2	My personal familiarity with an item influences my interest in the product	
	FA3	I prefer items that I have previously recognized or interacted with	
Trust	TR1	The recommender system improved my trust for shopping from this e-commerce	[11], [54]
	TR2	I feel that this recommender system is trustworthy	
	TR3	I can trust the performance of this recommender system to be good	
Continuance Usage Intention	CU1	I will use this recommender again, if I had to do a similar task.	[38], [51]
	CU2	I will use this recommender frequently, if I had to do a similar task.	
	CU3	I intend to keep using the e-commerce recommendation system in the future.	

To test the proposed structural research model, the study uses the partial least squares–structural equation modeling (PLS-SEM) method to test the research model, variable, indicator, and resulting data. Specifically, this research will use the statistical software SmartPSLS 4.0.9.8. These tests will include several differing data testing approaches, such as indicator reliability, internal consistency and reliability, convergent validity, discriminant validity (HTMT), and collinearity statistics (VIF) [65].

4. RESULT

4.1. Respondent Demographic

The data sample for this research came from respondents which answered an online questionnaire containing the questions described above, which is then filtered to only contain populations that lived in the Jakarta area.

Additionally, further steps were taken to ensure that all respondents have previous experience with using or shopping through an e-commerce platform. This questionnaire is spread and circulated via social media and other such online networks. Out of the entire populace, 116 respondents were used as a selected sample due to the limits of the SmartPLS 4.1.0.8. software.

The frequency and the percentage of respondents are presented in Table 2, this study selects respondents of e-commerce users in the area of Jakarta. The people who filled out the questionnaire are aware of recommendation systems in e-commerce. Table 2 illustrates that among the 116 respondents, 90 (81.1%) are female and 36 (18.9%) are male. Additionally, the largest number of respondents, 64 (30.7%), are from South Jakarta. This is consistent with previous data that South Jakarta has the highest internet usage rate (85.9%) of the population and (91%) of mobile phone users [66].

Moreover, it is important to note that the majority of respondents, 83 individuals (89%), are aged 18-25 years and are mostly university students. The collected data shows that the most used platform by respondents is Shopee, which is consistent with the findings of this study that Shopee has a very large user base in Indonesia, especially in Jakarta. The data shows that 98 respondents (84.5% of the total 116) have more than three years of experience in e-commerce usage. This suggests that the respondents of this questionnaire are generally familiar with e-commerce systems, including RS.

Table 2:Demographic of Survey Respondents

Criteria	Items	Frequency & Percentage
Age	<18 tahun	13 (11,2%)
	18-25 tahun	83 (71,6%)
	26-30 tahun	13 (11,2%)
	31-40 tahun	4 (3,4 %)
	> 40 tahun	3 (2,6%)
Gender	Pria	26 (22,4%)
	Wanita	90 (77.6%)
Domicile	Jakarta Utara	28 (24,1%)
	Jakarta Timur	10 (8.7%)
	Jakarta Selatan	64 (55,2%)
	Jakarta Barat	8 (6,9%)
	Jakarta Pusat	6 (5,1%)
Occupation	Mahasiswa	75 (64,7%)
	Karyawan Swasta	28 (24,1%)
	Pelajar	5 (4,3%)
	Others	8 (6.9%)
How long have you been using E-Commerce?	>3 years	98 (84,5%)
	1-3 years	13 (11,2%)
	<1 years	5 (4,3%)
Which E-Commerce do you use most often?	Shopee	70 (60,3%)
	Tokopedia	38 (32,8%)
	BliBli	1 (0,9%)
	Lazada	4 (3,4%)
	TikTok Shop	3 (2,6%)

4.2. Indicator Reliability

The first step in the analysis involves evaluating the results according to Indicator Reliability, a measure used to determine the appropriateness of each indicator as a measure of the variable and the general reliability of their usage. This is done by calculating the amount of variance in the indicators accounted for by the latent variable. As a rule, an outer loading value higher than 0.6 is acceptable 0.7 shows a reliable sign [67]. The indicators with scores ranging from 0. 4 to 0.7 may be retained if they increase the AVE and the composite reliability. According to some of the research, a score above the threshold of 0. 6 can be considered sufficiently reliable for research. However, it is widely agreed that indicators scoring below 0. 4 should be removed. After several analyses, the initial reliability coefficients of the research model are as follows:

Table 3:Initial Indicator Reliability Assessment

Aspect	Indicator	Outer Loading
Diversity of Suggestion	DS1	0.925
	DS2	0.899
	DS3	0.868
Suggestion Accuracy	SC1	0.855
	SC2	0.879
	SC3	0.848
Suggestion Novelty	SN1	0.774
	SN2	0.798
	SN3	0.815
Recommendation Quality	RQ1	0.872
	RQ2	0.844
	RQ3	0.863
	RQ4	0.877
Usage Attitude	UA1	0.897
	UA2	0.887
	UA3	0.891
Satisfaction	SA1	0.798
	SA2	0.887
	SA3	0.824
	SA4	0.854
Perceived Ease of Use	EU1	0.882
	EU2	0.855
	EU3	0.865
Perceived Usefulness	PU1	0.907
	PU2	0.882
	PU3	0.890
Familiarity	FA1	0.901
	FA2	0.835
	FA3	0.878
Trust	TR1	0.842
	TR2	0.853
	TR3	0.815
Continuance Usage Intention	CU1	0.857
	CU2	0.855
	CU3	0.815

From Table 3, the outer loadings of this model's values show that all indicators have no problem and are above 0.6 and ideal 0.7. This indicates that the indicators have been found to be reliable and that there is a strong relationship between each observed variable and its corresponding latent variable.

4.3. Construct Internal Consistency and Reliability

After that, the model's validity will be evaluated concerning Internal Consistency (the coherence of a model measured based on the interconnected patterns between the variables) and Reliability (the dependability of their latent variable measurements). The study will also evaluate and consider internal consistency and dependability when determining the validity, stability, and accuracy of a construct's model or instrument. The results of this assessment will determine by two critical criteria: Cronbach's alpha and Composite Reliability (CR).

Cronbach's Alpha refers to the unit used to measure the bottom limit of a construct's reliability, with a higher score indicating a higher level of consistency overall [68]. Thus, it is typically an indicator for the inter-relatedness of the items within the test, as well as the test item's possibility of error. The higher a Cronbach's score is, the lower the chance that a test result was generated through an error. This score is gained through the sum of extracted average variance/AVE scores and the squared correlations of the items within the study.

Meanwhile, Composite Reliability or omega coefficient measures the actual value of a variable's reliability through a composite scale, which means that it is measured using a series of items and subscales. It is typically judged as a better indicator of a structure's internal consistency [69]. The analysis was conducted using SmartPLS 4.1.0.8, which generates two composite reliability outputs: rho-a and rho-c. Rho-a measures the dependability of the model through a composite scale, which means it's used when all the variables are utilized to study the same underlying construct and not analyzing distinct aspects of the same thing. Meanwhile, rho-c is used when the variables used to study separate and distinct parts of a single construct, and it typically is a better indicator of reliability in such a case. Rho-c is frequently recommended over rho-a because reliability coefficients based on Structural Equation Modeling (SEM) generally yield superior results in a wider range of situations [70] . Since this study examines differing and segmented aspects of multiple items related to Recommendation Systems, rho-c will be used instead of rho-a.

The respective values of both Cronbach's alpha and Composite Reliability range from 0 to 1, with higher values indicating a higher level of reliability. A measurement that passes the threshold of 0.6-0.7 is generally accepted in more exploratory research. It must be mentioned, however, that values that are above 0.9 are generally judged as inadequate [71]. As seen in Table 4 below, all constructs have passed the acceptable threshold of >0.7 for Cronbach's alpha and composite reliability. This indicates that the model is adequately consistent and reliable for scientific studies. Therefore, it can be concluded from these measurements that all the variables in this research meet the requirements for validity and reliability tests using the SEM-PLS method, and thus fitting to be used within the model.

Table 4:Internal Consistency & Reliability

Variable	**Composite Reliability (rho_c)**	**Cronbach's alpha**
Diversity of Suggestion	0.925	0.879
Suggestion Accuracy	0.896	0.825
Suggestion Novelty	0.838	0.710
Recommendation Quality	0.922	0.887
Usage Attitude	0.921	0.871
Perceived Ease of Use	0.901	0.835
Perceived Usefulness	0.922	0.873
Satisfaction	0.906	0.862
Familiarity	0.905	0.842
Trust	0.875	0.786
Continuance Usage Intention	0.880	0.795

4.4. Convergent Validity Assessment

Next, the study will test the model's Convergent Validity, which measures the degree of similarity between a given test and other tests that claim to measure the same construct. The validity is determined by taking the Average Variance Extracted (AVE) of latent variables, which estimates a variable's indicator variance. It is commonly agreed that AVE values which are above 0.5 is considered as acceptable for a study [65]. The results of the analysis, as seen in Table 5 below, show that the model's AVE exceeds the >0.5 threshold and it thus deemed acceptable, which provides strong evidence to support the proposed research model. In addition, the items to measure the representation of underlying construction are correct.

Table 5:Convergent Validity Assessment

Variable	**AVE**
Diversity of Suggestion	0.805
Suggestion Accuracy	0.741
Suggestion Novelty	0.633
Recommendation Quality	0.747
Usage Attitude	0.795
Perceived Ease of Use	0.752
Perceived Usefulness	0.797

Satisfaction	0.708
Familiarity	0.760
Trust	0.700
Continuance Usage Intention	0.710

4.5. Discriminant Validity Assessment

The next test, the **Discriminant Validity** test, measures the degree to which the items within the model are distinct from one another. As the opposite side of the convergent validity test, this measurement also relies on the measured AVE value. Namely, it is taken into consideration through the Fornell-Larcker criterion, which posits that the square root of each variable's AVE must be greater than its highest correlation with other variables [72].

The results of the analysis, as shown in Table 6 below, indicate that all variables within the model have a higher AVE root than those correlated to other variables, and thus the model's results can be judged to be mutually distinct and valid.

Table 6:Discriminant Validity Assessment

	CU	DS	FA	FE	PU	RQ	SA	SC	SN	TR	UA
CU	**0.842**										
DS	**0.580**	**0.897**									
FA	**0.618**	**0.750**	**0.872**								
PE	**0.640**	**0.683**	**0.762**	**0.867**							
PU	**0.659**	**0.792**	**0.898**	**0.815**	**0.893**						
RQ	**0.658**	**0.718**	**0.757**	**0.844**	**0.778**	**0.864**					
SA	**.757**	**0.707**	**0.811**	**0.805**	**0.852**	**0.758**	**0.841**				
SC	**0.691**	**0.674**	**0.768**	**0.757**	**0.783**	**0.770**	**0.814**	**0.861**			
SN	**0.650**	**0.596**	**0.663**	**0.770**	**0.755**	**0.714**	**0.767**	**0.737**	**0.796**		
TR	**0.654**	**0.575**	**0.694**	**0.731**	**0.746**	**0.644**	**0.728**	**0.730**	**0.688**	**0.837**	
UA	**0.714**	**0.778**	**0.800**	**0.822**	**0.846**	**0.819**	**0.845**	**0.768**	**0.744**	**0.732**	**0.892**

4.6. Hypothesis Testing & Model Fit

The structural model will be tested through a model fit test, an examination used to investigate the overall fit of the model and avoid any specification errors. The first indicator of this test is the SRMR (Standardized Root Mean Square Residual) value of the model. The model's value sits at 0.120, which passed the general threshold of <0.10 [73] and is thus proven to be a good if slightly skewed fit. Furthermore, the model's Euclidean and Geodesic value have also fulfilled its criterion condition of exceeding 2.00 for d_ULS and exceeding 0.90 for d_G, sitting at 9.011 and 2.452 for d_ULS and d_G respectively. However, the NFI score for the model still sits below the ideal 0.9 score at 0.685, showing that the model fit remains within the boundary of reason yet suboptimal [74].

Therefore, further research and adjustments are needed to improve this value for future studies. Moreover, following recommendations from other studies, measurement of $R2$ values have been incorporated as a signifier of the predictive model's strength. The predictive model's strength is represented by these numbers, which go from 0 to 1. A higher number denotes a stronger model. However, it is generally acceptable to have a $R2$ value as low as 0.10 or 10% when working with things involving human actions and societal conditions [75], as human behavior is largely less predictable than static conditions. The values of this model are as listed in the following table:

Table 7:R-Square Value Results

Desc	R-square	R-square adjusted
CU	**0.596**	**0.589**
PU	**0.664**	**0.661**
RQ	**0.693**	**0.684**
SA	**0.714**	**0.712**
TR	**0.515**	**0.506**
UA	**0.791**	**0.786**

Furthermore, the model's Common Method Bias or CMB measure has been tested in order to ensure there are no strong indications of bias error. This measure is determined by the value of each variable's VIF (variance inflation factors), which must pass a threshold of being lower than 3.3 to indicate that it possesses little to no skewed or biased data. It must also score under 5.0 in order to ensure it has no potential collinearity issues [76]. As seen in Table 8, all variables possess VIFs that pass this criterion, and are thus judged to be largely unbiased.

Table 8:Collinearity & Common Method Bias

Item	Desc.	VIF
1	DS → RQ	1.910
2	SC → RQ	2.695
3	SN → RQ	2.279
4	RQ → UA	3.801
5	RQ → TR	2.345
6	EU → UA	4.465
7	EU → PU	1.000
8	PU → UA	3.246
9	UA → SA	1.000
10	SA → CU	2.125
11	FA → TR	2.345
12	TR → CU	2.125

4.7. Path Coefficient Testing Result

By utilizing the Bootstrapping method within the SmartPLS software to analyse the data gathered, it has been shown that the path coefficient yielded the following path coefficient, that has a value more than 0 and close to +1. For a more complete explanation, see table 9 below:

Table 9:Path Coefficient Testing Result

Hyp	Desc.	Path Coefficient	Result
H1	DS → RQ	0.318	Positive
H2	SC → RQ	0.369	Positive
H3	SN → RQ	0.253	Positive
H4	RQ → UA	0.298	Positive
H5	RQ → TR	0.276	Positive
H6	EU → UA	0.206	Positive
H7	EU → PU	0.815	Positive
H8	PU → UA	0.446	Positive
H9	UA → SA	0.845	Positive
H10	SA → CU	0.598	Positive
H11	FA → TR	0.485	Positive
H12	TR → CU	0.219	Positive

4.8. Hypotheses Testing Result

Finally, the results of the structural model showed that there is an acceptable fit between the proposed model and the data. Each of these models are then used to examine and determine the validity of all previously established hypotheses through their path coefficient, p-value, and t-value. The value listed within the table 10 is as listed below:

Table 10:Hypotheses Testing Result

Hypotheses	Description	t-value	p-value	Significance	Supported?
H1	DS → RQ	2.982	**0.003**	**	Yes
H2	SC → RQ	3.755	**0.000**	***	Yes
H3	SN → RQ	2.373	**0.018**	**	Yes
H4	RQ → UA	2.215	**0.027**	**	Yes
H5	RQ → TR	2.447	**0.014**	**	Yes
H6	EU → UA	2.072	**0.038**	**	Yes
H7	EU → PU	20.491	**0.000**	***	Yes
H8	PU → UA	4.142	**0.000**	***	Yes
H9	UA → SA	21.263	**0.000**	***	Yes
H10	SA → CU	6.978	**0.000**	***	Yes
H11	FA → TR	4.721	**0.000**	***	Yes
H12	TR → CU	2.461	**0.014**	**	Yes

Note: *** significant at $p < .001$; ** significant at $p < .05$; * significant at $p < .100$; NS = non-significant path.

H1: *Diversity of Suggestion* significantly affect *Recommendation Quality*

As indicated in the table above, it can be inferred that *Diversity of Suggestion* has a notable and predominantly positive effect on *Recommendation Quality* ($\beta = 0.318$, $t = 2.982$, $p < 0.05$). Therefore, *Diversity of Suggestion* is statistically significant in relation to *Recommendation Quality* and this hypothesis is considered **supported (at a confidence rate of 95 %) .**

H2: *Suggestion Accuracy* significantly and positively affects the *Recommendation Quality.*

As indicated in the table above, it can be inferred that *Suggestion Accuracy* has a notable and predominantly positive effect on *Recommendation Quality* ($\beta = 0.369$, $t = 3.755$, $p < 0.001$). Therefore, *Suggestion Accuracy* is statistically significant in relation to *Recommendation Quality* and this hypothesis is considered **supported (at a confidence rate of 100 %).**

H3: *Suggestion Novelty* significantly and positively affects *Recommendation Quality*.

As indicated in the table above, it can be inferred that *Suggestion Novelty* has a notable and predominantly positive effect on *Recommendation Quality* ($\beta = 0.253$, $t = 2.373$, $p < 0.05$). Therefore, *Suggestion Novelty* is statistically significant in relation to *Recommendation Quality* and this hypothesis is considered **supported (at a confidence rate of 95 %).**

H4: *Recommendation Quality* significantly and positively affects *Usage Attitude*.

As indicated in the table above, it can be inferred that *Recommendation Quality* has a notable and predominantly positive effect on *Usage Attitude* ($\beta = 0.298$, $t = 2.215$, $p < 0.05$). Therefore, *Recommendation Quality* is statistically significant in relation to *Usage Attitude* and this hypothesis is considered **supported (at a confidence rate of 95 %).**

H5: *Recommendation Quality* significantly and positively affects *Trust.*

As indicated in the table above, it can be inferred that *Recommendation Quality* has a notable and predominantly positive effect on *Trust* ($\beta = 0.276$, $t = 2.447$, $p < 0.05$). Therefore,

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Recommendation Quality is statistically significant in relation to *Trust* and this hypothesis is considered **supported (at a confidence rate of 95 %).**

H6: *Perceived Ease of Use* significantly and positively affects *Usage Attitude*.

As indicated in the table above, it can be inferred that *Perceived Ease of Use* has a notable and predominantly positive effect on *Usage Attitude* (β = 0.206, t = 2.072, $p < 0.05$). Therefore, *Perceved Ease of Use* is statistically significant in relation to *Usage Attitude* and this hypothesis is considered **supported (at a confidence rate of 95 %).**

H7: *Perceived Ease of Use* significantly and positively affects *Perceived Usefulness*.

As indicated in the table above, it can be inferred that *Perceived Ease of Use* has a notable and predominantly positive effect on *Perceived Usefulness* (β = 0.815, t = 20.491, $p < 0.001$). Therefore, *Perceived Ease of Use* is statistically significant in relation to *Perceived Usefulness* and this hypothesis is considered **supported (at a confidence rate of 100 %).**

H8: *Perceived Usefulness* significantly and positively affects *Usage Attitude.*

As indicated in the table above, it can be inferred that *Perceived Usefulness* has a notable and predominantly positive effect on *Usage Attitude* (β = 0.446, t = 4.142, $p < 0.001$). Therefore, *Perceived Usefulness* is statistically significant in relation to *Usage Attitude* and this hypothesis is considered **supported (at a confidence rate of 100 %).**

H9: *Usage Attitude* significantly and positively affects *Satisfaction.*

As indicated in the table above, it can be inferred that *Usage Attitude* has a notable and predominantly positive effect on *User Satisfaction* (β = 0.115, t = 2.751, $p < 0.001$). Therefore, *Usage Attitude* is statistically significant in relation to *Satisfaction* and this hypothesis is considered **supported (at a confidence rate of 100 %).**

H10: *User Satisfaction* significantly and positively affects *Continuance Usage Intention.*

As indicated in the table above, it can be inferred that *Satisfaction* has a notable and predominantly positive effect on *Recommendation Quality* (β = 0.598, t = 6.978, $p < 0.001$). Therefore, *Diversity of Suggestion* is statistically significant in relation to *Recommendation Quality* and this hypothesis is considered **supported (at a confidence rate of 100 %).**

H11: *Familiarity* significantly and positively affects *Trust*

As indicated in the table above, it can be inferred that *Familiarity* has a notable and predominantly positive effect on *Trust* (β = 0.485, t = 4.721, $p < 0.001$). Therefore, *Familiarity* is statistically significant in relation to *Trust* and this hypothesis is considered **supported (at a confidence rate of 100 %).**

H12: *Trust* significantly and positively affects *Continuance Usage Intention.*

As indicated in the table above, it can be inferred that *Trust* has a notable and predominantly positive effect on *Continuance Usage Intention* (β = 0.219, t = 2.461, $p < 0.05$). Therefore, *Trust* is statistically significant in relation to *Continuance Usage Intention* and this hypothesis is considered **supported (at a confidence rate of 95 %).**

5. CONCLUSIONS

5.1. Overall Interpretation

The resultant analysis of the data collected from 116 respondents, primarily aged 18-25 and predominantly university students with an average of over three years of e-commerce usage, indicates that the quality of recommendations in e-commerce systems is assessed based on three key aspects: *accuracy of suggestions*, *novelty of suggestions*, *diversity of suggestions*. These aspects are positive for the overall quality of recommendation systems, consistent with previous research that identifies these dimensions as important and reliable indicators of RS quality [11]. Between these factors, it was discovered that the system's Accuracy holds the highest effect on RQ, followed in importance and contribution by Diversity and Novelty. The finding implies that the most prominent factor in a user's assessment of a recommendation system's quality is the system's ability to give results that suit the user's taste and preferences, followed by the *diversity of the recommendation's categories* and the *novelty* of the recommended items, *respectively*. The findings also align with the results of a previous study, which posits that Accuracy is the most influential factor determining Recommendation Quality [77]. These findings differ from those of prior studies, which demonstrated through quantitative research that diversity is the most significant factor in determining an RS quality's influence over initial purchase decisions [11] Prior studies indicated that RSs with a more diverse set of suggestions and categories generates a higher level of attraction for customers and possess a higher influence on their intial shopping interest. In contrast, the results of this study differs, indicating that the RS's accuracy is the most influential indicator of an RS's quality when it comes to long term engagement.

This distinction highlights a key difference between the objectives of previous studies and the focus of this research. Diverse suggestions are generally regarded as more effective in terms of generating initial purchasing decisions [11]. However, when the system aims to gain long-term use or generate continuance usage intention, accurate and customer aligned suggestions are considered more influential. This phenomenon indicates that a more diverse set of options possess a broader appeal to customers, allowing them to entice them to take the first purchases. However, it is less reliable as a long-term engagement method, as it loses its influence as the novelty effect wanes. In contrast, a higher level of accuracy fosters a more reliable and consistent performance, encouraging users to return and maintain long-term usage. A more accurate recommendation list also has a higher chance of catching the user's interest and retaining their engagement, as the items shown would resonate with them more than a more varied or novel selection. One possible explanation of that Accuracy plays a crucial role in balancing the positive aspects of both Novelty and Diversity. While both elements focus on providing a wider spectrum of recommendation suggestions from different categories or previously unseen items, Accuracy ensures that these recommendations remain relevant. If unmitigated by Accuracy, the recommendations risk being flooded by irrelevant or unrelated suggestions, diminishing their value. The quality of the recommendations provided by RS also has a large influence on users' trust in the system. In particular, the findings indicate that the RQ perceived by the user increases users' trust in the RS and their willingness to continue using it. These results correlate with a previous finding, which also stated that RQ holds a significant effect on the user's trust in the system [54]. This likely indicates that the more the recommendation lists align with the user's needs, the more likely it is that users will experience a better and put their trust on the system's service. The prior study also suggested that a higher degree of trust allows the user to treat the system as credible for long-term use and will be more willing to use the system again in their future services [10].

The analysis also shows that the Quality of the RS does not yield the highest influence on the user's Usage Attitudes, indicating that while quality plays an effect on the user's acceptance and consideration of system usage, other factors still play an equally significant role in determining a user's attitude and long-term use. These factors include the interdependent Technology Acceptance Model (TAM) factors Perceived Ease of Use and Perceived Usefulness, which have both been found to positively and significantly affect users' attitudes toward using the system, like previous studies [55]. However, Perceived Usefulness has been noted to have a higher effect on user usage attitude than Perceived Ease of Use and even Recommendation Quality. These results are in line with the findings of a previous study, which also found that the effects of TAM factors on Usage Attitude, especially Perceived Usefulness, does yield significant influence over Usage Attitude [78]. These results support the implication that users prioritize the system's practical utility over usability or recommendation quality in their evaluation of the system. These findings also imply that a level of usability, navigability, and recommendation quality might already be expected as a baseline by the user and might have a diminished or muted impact on the user's mood compared to overall usefulness.

In addition, RS Quality's effect on Usage Attitude is significantly weaker than its influence over Satisfaction. This implies that while the RS's quality is a key predictor of the user's level of enjoyment, it is a relatively lesser indicator of their overall disposition. It was also concluded that Usage Attitude is significantly influenced by other TAM factors (Perceived Ease of Use and Perceived Usefulness) in a greater way than the TAM variable's effect on Satisfaction, which was established by previous research [11]. More specifically, the effects of TAM factors on Usage Attitude are approximately twice as strong as their correlation to Satisfaction. This is purported to be caused by the inherent structure of the TAM framework. Within the framework, Usage Attitude is directly connected to and shaped by the perceived usefulness and ease of use of the system, reflecting the user's disposition regarding the technology. Meanwhile, Satisfaction primarily reflects the engagement or fun the user experiences when using the product, which is comparatively narrower in scope.

The findings have further confirmed the significant and positive role of Satisfaction and Trust in influencing a customer's Continued Usage. These

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findings are consistent with those of prior studies [10]. which similarly purports that both Satisfaction and Trust are strong predictors of prolonged or long-term system use. The research also observed that user Satisfaction was significantly influenced by Usage Attitude, implying that a positive attitude towards the system can increase overall user satisfaction with it and their intention to continue using the recommendation system. It can be surmised from this that the attitude held by the user and their overall perception of the system, as previously determined by its Quality, Ease of Use, and Usefulness, holds significant sway over the satisfaction the user feels. This Satisfaction would then increase the user's intention to continue using the system, as a higher-level satisfaction would correlate with a more positive experience, giving the user further incentives for future or continued use. These findings fall in line with the results of prior research, which similarly suggested that a higher level of enjoyment or fulfillment would result in increased encouragement for future use of the product in a significant manner [57]. However, the results also reveal that Satisfaction exerts a stronger effect on Continuance Intention than Purchase intention, while Trust has a considerably diminished effect on Continuance Intention compared to its impact on Purchase Intention. This result suggests that while Trust plays a crucial role in initial transactional decisions, it becomes less significant in retaining ongoing usage. This also implies that a customer's day-to-day engagement of the system is more strongly driven by the user's enjoyment or fulfilment.

Both Trust and Satisfaction's dynamics on Continuance Intention were also found to be massively influenced by TAM aspects. While previous works have shown that Trust exerted a higher degree of impact on continued usage intention compared to satisfaction [11], the present findings suggests that within the context of technological adoption, Satisfaction's impact far exceeds the that of Trust. This shift is likely caused by the unique characteristics of technological adoption environment. Within such a context, user Satisfaction is often linked to the ease of use, perceived usefulness, and overall user experience, which are all key components of TAM. In contrast to traditional contexts, Trust is largely uninvolved in TAM aspects, indicating that it plays a lesser role in the adoption and continued usage of e-commerce technology, which instead relies more on immediate benefits and gratification the system can provide. Satisfaction, as the encapsulation of the users enjoyment and evaluation of the technology, therefore emerged as the stronger predictor.

Lastly, analysis shows that the *Familiarity* of users with the products recommended by the system strengthens their trust, suggesting that the more familiar a user is with the system or its contents, the likelier it is for them to trust it. This result falls in line with the conclusion of previous works, which also suggested that the Familiarity of a person with the recommendation system arouses a feeling of trust through repeated exposure or previous connections [11] .As previously discussed, trust positively affects the users' intention to continue using recommendation systems in the future and thus continue engaging in it. As such, Familiarity is imperious in fostering the trust of users and must be catered to by e-commerce and RS developers alike in order to establish a continued engagement with their user bases.

All in all, the purpose and goals of this study have been fulfilled by the results of the above analysis. The main objective of this study was to assess the public's reception of existing recommender systems in e-commerce. To Achieve this, a comprehensive review of the literature on recommendation systems, customer behavior, and relevant information systems (IS) theories was conducted. This review included a critical analysis of public's perceptions of recommendation systems, highlighting key factors that influence user acceptance and satisfaction. In particular, the Technology Acceptance Model (TAM) theory was employed as a foundation for the theoritical framework, owing to its significance in evaluating ease of use, perceived usefulness, and user attitudes toward the system.

The second objective of the study was to determine the factors that significantly contribute to the effectiveness of recommendation systems. Using previous studies as a basis, this study identifies Diversity of Suggestion, Suggestion Accuracy, Suggestion Novelty, Recommendation Quality, Usage Attitude, Perceived Ease of Use, Perceived Usefulness, Satisfaction, Familiarity, Trust, and Continuance Usage Intention as factors playing a significant role in shaping customer reception and intention to utilize e-commerce recommendation systems. These findings were then developed into several hypotheses, constructed into a theoretical framework, and validated via quantitative analysis to accomplish this objective. Through structural equation modeling using the Partial Least Squares

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(PLS), the study has confirmed the relationship between these factors and their effects on the system's effectiveness, as well as their cumulative effect on customer behavior. Among all these factors, Accuracy was determined to have the largest impact on the RS's perceived overall quality, Perceived Usefulness was found to be the most prominent factor behind positive Usage Attitude than both Quality and Ease of Use, Satisfaction was identified as wielding a larger impact on Continuance Intention than Trust.

The third objective of this study was to assess the impact of TAM factors and RS quality on a customer's Usage Attitude. The findings show that the quality of an RS yielded a significant influence over Usage Attitude, but this effect is lesser than their direct effect on Satisfaction. This implies that while an RS's quality is a good indication of the user's overall feelings about the product, positive or negative, it's less able to depict the narrower scope of user enjoyment. TAM factors such as Perceived Usefulness and Ease of Use also significantly affect Usage Attitude more than they do Satisfaction, implying that user reception is more accurately predicted by technological adoption factors than user enjoyment. The fourth objective was toexamine the mediating role of Usage Attitude on Satisfaction and Trust in influencing Continuance Intention. The results shows that Usage Attitude possesses an extremely high influence on Satisfaction. A likely cause of this is the fact that the user's approach to the technology's use includes all positive and negative reactions to it, which means it covers the user's engagement and sense of fun as well. Its also determined that Satisfaction possesses a greater influence over Continuance Intention than it does on Purchase Intention, making user enjoyment a high-priority focus for long-term use oriented systems. Trust, although a primary element of short-term purchase intentions, yields a critical yet relatively lesser effect on long term continuous usage.

5.2. Implications

This Result of the research is expected to become benefit for:

5.2.1. Recommendation system developer

One of the goals of this research is to motivate RS developers to focus on developing systems based on the factors identified in the study. RS aims to help users find products that meet their needs or introduce them to new options to improve their experience. Based on the study's findings, the RS's quality and helpfulness are typically determined from three primary factors: Uniqueness of the recommendations, Diversity of products suggested, and Accuracy in aligning with user's preferences. Among the three factors, Accuracy is determined as the most crucial factors behind RS quality, followed by diversity and uniqueness as secondary factors. As such, developers should prioritize increasing the accuracy of their RS systems through a more personalized and fitted algorithm. For example, new recommendations should integrate algorithms that consider evolving trends and changing user preferences to reduce inaccuracies and provide a highly personalized selection of recommended items that better fit the user's needs. To this end, developers should incorporate real-time feedback loops and behavioral analytics capable of refining the RS's results in real-time in accordance with the user's current behavior. Additionally, developers should also prioritize not only on accuracy, but also on its Diversity and relevance in order to reduce the user's dissatisfaction with overfamiliar suggestions and prevent user fatigue. Diversity's emergence as the second most influential factor behind an RS's quality also signifies that developers should work on RS that are not just accurate, but able to offer consistently broad and varied options to users, thereby exposing more purchase ideas for users to make use of during their shopping experiences and encouraging continued system usage.

In addition, the study also confirms a previous study's conclusion that the RS's quality also positively affects Trust, which in turn plays an integral role in raising a user's Intention to Continue using the system [11]. The study also reveals that the user's Familiarity with the products the RS offers or even the RS mechanic itself has a massive influence over their level of Trust regarding the system, due to the sense of safety and reliability it provides. As such, Familiarity is imperious in fostering the trust of users and must be catered to by e-commerce and RS developers alike to establish a continued engagement with their user bases. From the developer's side, the system should be optimized to regularly suggest items that are familiar and aligned with the user's prior preferences, as it can establish a sense of reliability and predictability, making users more comfortable with the system. However, this Familiarity must also be tempered with a high degree of Accuracy and Diversity through the RQ, in order to ensure the selection does not remain stale and striking the right balance to maintain both trust and user interest. Developers can achieve this by utilizing user profiling systems capable of incorporating not just historical data in the RS's analysis, but also contextual factors such as product trends, device usage, location, time, and user demographic. Moreover, developers may also introduce a sense of transparency into the RS's design to help users understand by certain recommendations being shown to them. For example, the system may provide a clear explanation on why a certain item are shown in their inbox, such as "Recommended because you liked Item A" or "Item is trending in your region", to make users feel more connected to the system.

5.2.2. E-Commerce platforms

The purpose of this study is to assess the factors that have the most impact on the effectiveness of RS. Prior research has shown that about 35% of the sales on Amazon [41] are attributed to the recommendation system, which underlines the importance of RS for e-commerce platforms. In addition to increasing sales, RS can help users to choose the products they need and that they are interested in, which will encourage further use of the system. To maintain user interest over time, e-commerce platforms need to regularly update their RS algorithms to reflect evolving shopping trends and individual user preferences. As user tastes and preferences are dynamic, a static or outdated algorithm can lead to diminished relevance of the recommendations, causing users to disengage from the system. In addition to the algorithmic changes brought in through the RS developers, future e-commerce platforms may supplement this continuous adaptation by offering in-platform methods to garner user data and inputs. For example, the platform might record recent interactions, seasonal changes, search/click data, browsing patterns, and emerging trends connected to the user's profile. In addition, they may include integrated user measurement methods such as Dislike or Like buttons, personalized surveys, rating pop-ups, or even providing a way for users to filter their own recommendations based on certain criteria or categories. By ensuring that the system evolves in tandem with the users' changing needs, e-commerce platforms can maintain a high level of engagement and satisfaction, ultimately driving repeat visits and purchases.

Moreover, the study's results indicate that the user's Perceived Usefulness and Perceived Ease of Use also play a large role in determining the user's Attitude towards RS usage. To facilitate a higher degree of Ease of Use, e-commerce platforms could implement a smoother and more seamless user interface and menu to ease their platform's navigability. In addition, a smoother interface can help reduce the cognitive load placed on the user. Cognitive load refers to the mental effort required to process information, and if this load is too high, users may become frustrated or overwhelmed with the information provided, leading to disengagement. By introducing a more intuitive menu, the users would be able to digest the information provided by the RS easier, allowing them to engage more with the presented recommendations. E commerce can also boost the RS's Perceived Usefulness by adding features that could help the user find better recommendation results, such as a way to compare products and filters the user can adjust. These features would allow users to find greater use in the RS, increasing their likelihood of present and continued usage. In addition, platforms may also leverage the positive effects Trust (as bolstered by Familiarity) has on Continuance intention by adjusting this connection by incorporating E-commerce platforms with a more personalized interface, adjusting the layout and appearance of the recommendations list based on user behavior. This would allow the user to slowly feel a sense of familiarity with their website feed by surrounding them with familiar elements and item choices, providing the user with a better and more immersive experience.

5.3. Limitation & Future Work

The study's primary objective is to study and explore the relationship between RS quality and usage attitude, the connection between sociological factors and RS user perception, as well as their correlative impact on user satisfaction and continuance intention. While the preceding discussions have already tackled these objectives, several limitations remain regarding the study's scope and execution. Firstly, the study's scope focuses heavily on social or humanistic elements that influence RS algorithm reception and user satisfaction, such as user trust in the system, user familiarity with the RS elements and recommended product, and their overall attitude regarding the system's usage. However, this heavy focus may cause the results to overlook critical technical or algorithmic aspects that may play a crucial role in shaping the workings of an RS systems, such as model architecture, optimization techniques, and computational effectiveness/efficiency. The results of this study also only indirectly explored the potential interactions between an RS's technical and sociological factors, merely covering the influence that algorithmic factors have on sociological

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components through the mediating effect of RS quality, which these technical factors influence heavily. Future studies could cover this gap by integrating the findings of this study with other works covering the technical aspects of RS. This would allow them to create a more thorough analysis of both sociological and technical factors and map out their interactions and correlations with one another, providing a more complete understanding of RS mechanics.

Secondly, the case study's focus on RS mechanics and factors within the e-commerce domain may limit the generalizability of its findings on other contexts or industries. For example, business fields such as online streaming services and e-learning platforms might find it challenging to apply these results on their RS systems, as the study's findings are written for and tested with e-commerce data. In addition, sociological factors such as user preferences and trust networks may vary significantly across regions and domains, and as such the findings of this study might not be fully relied upon outside of its scope. As the study's scope are limited to the e-commerce market of Indonesia as represented by the population of Jakarta, future studies should aim to further expand the scope through a more extensive empirical investigations to both help validate these results and enhance their applicability. By expanding the scope of such a study by including a more varied category of industries and areas, future analysis might yield a result that is more generalizable, relevant, and applicable across different contexts. Future works should also consider incorporating comparative analysis that consider other perspectives and factors that might hold influence over the inner workings of an RS, such as personal user influences like background or cultural factors. They may also explore logistical issues that might be encountered in real RS implementation, such as privacy concerns regarding the data collection necessary for the demographic analysis required to run a sociological-based RS and potential biases in the RS's demographic analysis. By building upon the limitation of this study, future researchers may cover grounds which have not been explored within this work and develop more conclusive theories and RS constructs that offer a higher standard of quality and client satisfaction levels.

Data Sharing: Data described in the manuscript, code book, and analytic code will be made available upon request pending application and approval.

Statement of authors' contributions to manuscript: RAY and GW designed the study; RAY performed the literature review; RAY analyzed data; RAY and GW wrote the paper; All authors assisted in the interpretation of results, were involved in the critical revision of the article, and read and approved the final manuscript.

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