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Does metaverse improve recommendations quality and customer trust? A user-centric evaluation framework based on the cognitive-affective-behavioural theory

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A B S T R A C T

Recommendation agents (RAs) have proven to be effective decision-making tools for customers, as they can boost trust and loyalty when customers shop online. They can analyse large amounts of data using machine learning algorithms and predictive analytics capabilities to provide highly relevant recommendations to users. In previous studies, several approaches have been implemented to refine and assess the effectiveness of these agents. As a new form of virtual reality universe, metaverses can be seen as a new venue for improvements in the performance of online RAs. By exploiting the capabilities of the metaverse and incorporating data about the user's behaviour and preferences, the performance of these systems can be enhanced in terms of the accuracy, diversity, and novelty of the generated recommendations. The metaverse can provide visually appealing and interactive recommendations, and there are several potential factors that can affect the customer's experience. The cognitive-affective-behavioural theory is used to develop the proposed research model. This study investigates the impact of the capabilities of the metaverse on three quality factors of RAs: diversity, accuracy, and novelty. The influence of the quality of the recommendations on affective trust and the influence of affective trust on customer loyalty are also examined. In addition, as this is an emerging technology, perceived privacy plays a crucial role in maintaining users' trust and confidence. Hence, the moderating influence of perceived privacy on the relationship between the quality and affective trust of RAs is examined. The moderating impact of product knowledge on the relationship between the individual perception of trust and loyalty is investigated. Data were acquired from 288 Malaysian respondents and analysed using the PLS-SEM method. The findings of this study show that the capabilities of the metaverse have favorable impacts on several quality factors of the recommender system, including accuracy, diversity, and novelty. Furthermore, these quality factors impact the perceived quality of RAs, which in turn impacts customer trust and loyalty. Perceived privacy acts as a moderator on the relationship between the quality of recommendations and the individual's perception of trust.

Introduction

An automated recommendation system, also called a recommendation agent (RA), analyses the data associated with a user and suggests products, services, and content based on the user's personal preferences (Bagherifard et al., 2017; García-Sánchez et al., 2020; Gharahighehi et al., 2021; Nilashi et al., 2020). There are many applications for these agents in domains such as e-commerce (Khan et al., 2021), media (Herce-Zelaya et al., 2020; Nilashi et al., 2023), travel (Renjith et al., 2020), news (Karimi et al., 2018), and entertainment (Airen & Agrawal, 2023). RAs are also playing an increasingly crucial part in individuals' decision-making procedures (Scholz et al., 2017; Wang et al., 2022), especially in the context of online retail and e-commerce. An RA can offer valuable assistance to customers in the highly competitive environment of e-commerce (Guo et al., 2014), where there is a vast array of options that often overloads the user's capabilities (Liu et al., 2022). In this case, an RA can assist the user in

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finding products that will meet their specific needs and preferences more rapidly and easily.

These agents can analyse vast amounts of data with the help of machine learning algorithms and predictive analytic capabilities, and can provide highly targeted and relevant recommendations that can increase customer loyalty and satisfaction. An RA works by analysing user data (e.g., browser history records, search queries, and past purchases) in order to build a profile of the user. To generate the list of recommendations for the user, the RA uses various algorithms such as collaborative filtering (CF) (Kuo & Li, 2023), content-based filtering (CBF) (Afoudi et al., 2021), and hybrid approaches (Biswas & Liu, 2022). In a CBF algorithm, the suggested items are similar to items the user has previously purchased, while a CF algorithm recommends items that are common among similar users (Afoudi et al., 2021). The fundamental idea behind CBF is to suggest new products based on their attributes and the historical preferences of the customer (Kuo & Cheng, 2022). Hybrid recommendation approaches combine both CF and CBF to provide more precise and personalised recommendations (Tewari, 2020). The use of RAs has increased customer engagement, retention, and revenue to many well-known online shopping platforms, such as Amazon.com, Alibaba.com, and Shein.com. However, the efficiency of an RA is determined by the quality of the data and the algorithms used to generate recommendations. Users who are provided with inaccurate or irrelevant recommendations may lose trust in the agent and the company as a whole.

The primary objective of an RA is to provide customised selections to users based on their preferences, interests, and past behaviour, where several interrelated factors will impact on individuals' perceptions of the quality of the generated suggestions. The accuracy of an RA is very important, as this has a direct impact on the quality of recommendations provided to users (Zanon et al., 2022). Inaccurate recommendations will negatively impact the users' trust in these systems (Nilashi et al., 2016), which can lead to a decrease in an individual's engagement and usage behavior. Previous studies have shown that the accuracy of recommendations can have a significant impact on their overall performance. Scholars have worked on other various aspects of the design of RAs in order to improve user experiences such as diversity and novelty. Diversity represents the system's capacity to offer a variety of products, with the aim of broadening the consumers' preferences (Zanon et al., 2022). Another important factor is the novelty of the recommendations: an item that exactly matches the needs of the customer is hardly a suitable choice if the customer is already very familiar with it (Kunkel & Ziegler, 2023). A successful RA should be able to nudge users out of their "comfort zone", allowing them to enjoy novel, diverse, yet still pleasant experiences (Gravino et al., 2019).

The accuracy of recommendations is affected by the quality of data. Data collection methods, preprocessing techniques, and integration processes all affect the quality of the data used in RAs, meaning that it is essential to ensure that the data used are precise, relevant, and up-to-date. Previous studies in the literature have reported that the sparsity problem (a lack of information about users' preferences, interests, and behaviour) has a major effect on the accuracy of recommendations (Heidari et al., 2022; Joorabloo et al., 2021). Most RAs suffer from this problem, as only a small percentage of items are rated by users and there are limited numbers of interactions between users and items. Furthermore, biased recommendations that favour popular items over less popular ones can result from a sparse dataset, potentially leading to a loss of diversity in recommendations (Geng et al., 2023). RAs may not be able to accurately detect the users' needs and preferences, and addressing this issue in the context of recommendation systems is an important area of research.

The level of user engagement with an RA can be improved with the help of emerging digital technologies (Margaris et al., 2018). Previous research has suggested that the use of social media data to enhance the performance of an RA can yield improved results (Nilashi et al., 2023), and to achieve this, RAs can be connected to various online communities, meaning that users of social networking sites have many options for reviewing and rating products purchased online (Vazquez et al., 2023). Textual feedback can be used as a complement to user ratings, in order to enhance the quality of the data and the accuracy of recommendations, thereby ensuring that they are tailored to the preferences of the users (Nilashi et al., 2023). In addition, connecting RAs to popular social media sites may encourage more people to use them by making it easier for them to recommend services to their friends and followers.

As an emerging technology, the metaverse offers new opportunities for the enhanced operation of RAs and the delivery of more correct and relevant suggestions to users. As a result of the intersection between the real and virtual worlds in the metaverse, unique mechanisms for both generating and perceiving value have emerged (Mancuso et al., 2023). With the integration of several innovations within the metaverse (El Hedhli et al., 2023), the recommendations can take novel and unexpected forms in terms of design, presentation, and implementation. Insights into user preferences and attitudes can be gained through the metaverse's virtual setting, which allows users to interact in real time, both with each other and with digital items. The capabilities of the metaverse in terms of data availability and enrichments can enhance the performance of RAs, which accordingly influences the user's overall experience. However, further investigations are essential in order to understand the possible impacts of the capabilities of the metaverse on the ways in which users perceive the different quality factors of RAs.

The promising capabilities offered by the metaverse are associated with significant privacy concerns, which can have a significant impact on the customer's experiences and the adoption of technology. Privacy concerns have been linked to several outcome variables in the literature, including the acceptance of technology in healthcare (Dhagarra et al., 2020), trust, intention, and attitude towards search engines (Palanisamy, 2014), and customer loyalty toward online shopping (Wong et al., 2019). The metaverse primarily offers customers granular services based on multiple dimensions of interaction, in which data are collected from numerous venues, unlike the data gathered from a single venue by conventional internet apps (S. Zhang et al., 2023b). In general, businesses gather customers' private information to execute transactions as well as to better comprehend their needs, requirements, and choices, so that they can tailor their advertising campaigns to them (Degutis et al., 2023). Privacy concerns grow with the implementation of RAs, as the volumes of data gathered and the user profiles expand, to provide classifiers with more data for learning and inference (Slokom et al., 2021). The huge volumes of personally identifiable information that will be exposed if the privacy of a Meta application is compromised will be much greater than for conventional Internet applications, thus posing a severe risk to consumers' privacy (Liu et al., 2021; Wang et al., 2021). In a survey conducted by Statista (2022a), 87 % of American citizens said they would be worried about their privacy if Facebook were to be successful in building the metaverse. In addition, 50 % of those surveyed said they were concerned that hackers would be able to impersonate other people too easily, and 41 % believed it would be too difficult to preserve their true identity in the metaverse.

Due to these uncertainties, the acceptance of RAs in the metaverse will require a certain level of familiarity with and comprehension of the products involved. Customers must be knowledgeable about the products they interact with, as the metaverse's capabilities are developed further. In traditional RAs, the level of knowledge of the product will impact how the customers perceive the quality of the recommendations (Yoon et al., 2013). Based on the above discussion, we can draw up the following research questions:

i. *How do metaverse capabilities influence various quality factors of recommender agents (RAs)?*

ii. *How does perceived privacy affect the relationship between recommendations quality and customer affective trust?*

iii. *How does product knowledge influence the relationship between customer affective trust and customer loyalty?*

The remainder of this research is structured as follows: Section 2 introduces the Cognitive-Affective-Behavioural theory as the theoretical foundation of the study. Section 3 presents an overview of metaverse capabilities in retailing. Hypothesis development is detailed in Section 4. The study methodology is outlined in Section 5, and the results are discussed in Section 6. Finally, Section 7 presents the conclusion and the research contributions of the study.

Theoretical background

Cognition-affect-behavioural model

Together with the theory of planned behavior (Ajzen, 1991), the technology acceptance theory has been deployed as a theoretical base in several contexts to appraise an individual's early acceptance of information systems, innovations, and tools (Davis et al., 1985). However, early acceptance cannot truly reflect the system's performance, as a long-standing relationship between the users and the system is the true measure of the system's performance (Bhattacherjee, 2001). Researchers have therefore considered a three-stage sequence of continuous intention, from quality features to long-standing commitment (Frank et al., 2014). Lazarus (1991) explored the impact of the appraisal of interior and contextual variables on the affective response, which in turn influences coping actions. Drawing on Lazarus (1991) framework of appraisal, Bagozzi (1992) investigated the link between attitude and behaviour based on the intercession of affective variables between the cognitive appraisal and the coping response. Bagozzi (1992) stressed the prominence of the motivational link between attitude and behavior in forming a user's desire to perform an action. Perusing this line of research, Eagly and Chaiken (1993) presented the attitude formation theory, in which attitudes are formed solely based on the impact of three folds: cognition, affect, and behavior. Expanding on this theoretical framework, user behavior is assessed using a three-tiered chain model. The knowledge that users gain about the technology through cognitive variables will formulate their views. As the consumer engages with the technology, cognitive variables are framed to develop beliefs. The level of experience with the innovation creates a feeling of emotional desire that frames the emotive perceptions. This theory highlights the intervention of emotive perceptions between beliefs and actions. Users' emotional perceptions can be influenced by their positive or negative evaluation of the technology, which in turn shapes their affective response (Kwon & Vogt, 2010).

In this research, we adopt the cognition-affect-behaviour model to explore the factors that influence a customer's loyalty toward an RA in the metaverse across three structured layers: (i) the appraisal of the quality of the recommendations (cognitive), represented by diversity, novelty, and perceived accuracy; (ii) the affective component, represented by trust; and (iii) the behavioural component, represented by loyalty.

Cognitive overload theory

Individuals may feel stressed and mentally exhausted if their cognitive load exceeds a particular limit (Pang & Ruan, 2023). Information overload may result in negative effects such as information anxiety, information fatigue, and tension (Islam et al., 2022). According to cognitive load theory, humans have limited mental capacities, and a cognitive load that is too high will impact their ability to acquire information about products or services, leading them to have negative opinions towards a good or service. Individuals are described as 'cognitive misers' who frequently hesitate to put forth more effort than is essential. RAs have proven their effectiveness in addressing the problem of information overload in traditional online environments.

The problem of information overload has been linked to e-commerce in several contexts (Fang et al., 2021) where the environment in which the customer processes the information influences their perceptions of products and services. In situated cognition theory, rather than serving as an intangible mental process, information processing is thought to take place internally and actively based on the environment in which the customer is located (Semin & Garrido, 2015). Users can better understand the value of a product or service when their experiences enable them to relate intangible facts to actual interactions and real-world events (Fan et al., 2020). Online shoppers often have difficulty in seeing how things will fit into their own unique environments (Jung et al., 2015), which increases their mental workload. Hence, if the cognitive load is too great, users will experience negative emotions as a result of the gap between their desires and the influence of their surroundings, which will have a detrimental impact on their ability to make decisions (Liu & Goodhue, 2012).

In the metaverse, this challenge can be addressed by providing an immersive environment where users can interact with products or services in a realistic and contextually relevant manner. Metaverse recommendations can help individuals overcome the problem of information overload in different ways, as they can provide a greater resemblance to individuals' interactions and interpretations of objects in the real world. These recommendations allow customers to overlay virtual information onto their actual surroundings, thus reducing the cognitive load required to understand how a product will fit into their personal contexts.

Metaverse capabilities in retailing

Although there is no single agreed-upon description of the metaverse, most experts concur that it is a network of interconnected virtual settings in which individuals can engage to mimic activities in the real world (Park & Lim, 2023; Zallio & Clarkson, 2022). As the name suggests, the metaverse is not only a virtual venue but a point at which the real and virtual worlds meet. The metaverse is also made up of a collection of different platforms and innovations that work together to provide users with an experience that unites both the real and the virtual realms (Hazan et al., 2022). Through a combination of diverse technical infrastructures, a fully developed metaverse can create a parallel environment for cultural exchange and human engagement (Stephens, 2021). Developments in the metaverse have been facilitated by the huge advancements in the areas of artificial intelligence (AI), big data (BD), virtual reality (VR), and augmented reality (AR), which are all used to enhance the actual environment and enhance the consumer's experience in the metaverse (Park & Lim, 2023). All of these technological innovations are crucial for creating and enhancing immersive realities, as they allow individuals to engage with telepresence, which often affects the level of immersion in the metaverse environment (Giang Barrera & Shah, 2023). The metaverse should provide individuals with a realistic experience and enable them to be immersed in the virtual world (Dionisio et al., 2013).

The capabilities of the metaverse are expected to cause shifts in the shopping experiences of individuals in both the digital and physical retail sectors by providing them with engaging and immersive knowledge about goods and services (Klaus & Kuppelwieser, 2023; Serravalle et al., 2023). Since they can break down the social and physical barriers between customers and brands, the metaverse and other fully immersive technologies have the opportunity to stand alone as innovative advertising instruments (Chekembayeva et al., 2023). Luxury businesses can use social media to communicate with clients in the metaverse and apply digital advertising strategies to enhance their performance (Pangarkar et al., 2023). VR, as a promising tool for experiencing the metaverse, is growing in popularity among businesses (Sadamali Jayawardena et al., 2023); for example, Gucci has introduced ‘Gucci Town,’ an interactive environment within the realm of the metaverse. The interactive components of Gucci Town include minigames, browseable art gadgets, and the Gucci store, in which consumers can purchase clothes for their avatars. In order to create highly realistic and enjoyable shopping experiences that are appealing to customers, some merchants have started working with game designers, who were early pioneers in the realm of retailing in the metaverse (Yoo et al., 2023). For instance, Uniqlo collaborated with video game developers from Mojang Studios to create a collection of T-shirts with the Minecraft theme, which were later made available in the physical world as well as in online Minecraft marketplaces (Waters, 2020). The existence of avatars is a crucial element that differentiates the experience in the metaverse from earlier online environments. Metaverse systems provide 3D avatars that reflect the individual’s personality, and can be viewed by other individuals, in contrast to current virtual worlds where individuals are identifiable by their cardinalities and photos. Platforms have integrated avatars with various capabilities to improve online interactions, due to the importance of these avatars in the realm of the metaverse (Kim et al., 2023). Recent studies indicate that virtual influencers on social media achieve a significantly higher engagement rate compared to human influencers, and this trend is expected to intensify with the emergence of the metaverse and the increased prevalence of VR (El Hedhli et al., 2023; Li et al., 2023).

Research model and hypotheses

Capabilities of the metaverse and the novelty and quality of RAs

The degree to which recommendations are perceived as new, surprising, or unexpected by a user is referred to as novelty (Ali Abumalloh et al., 2020). Providing a suitable level of novelty is a difficult task for RAs, as it necessitates striking a counterbalance between the investigation of new products and the use of previously established preferences, while also maintaining a specific accuracy level. The usage of the metaverse can improve the novelty of recommendations by providing a rich and diverse environment in which user interactions and preferences can take place. In the metaverse, users will be able to interact with other users in ways that are not possible in the real world (Dong et al., 2023). In addition, users of the metaverse will be able to communicate with each other in a variety of ways, such as through chatting and sharing information regarding products, thereby opening up new avenues for both retailers and consumers (El Hedhli et al., 2023). These interactions have the potential to generate a huge volume of information regarding the users’ preferences, behaviours, and relationships, thereby enabling the metaverse to exploit users’ previous preferences. The data collected in this way can then be employed in the datasets of an RA to optimize the novelty of the selections. For instance, an RA could make use of information gleaned from user interactions in a digital shopping mall to make recommendations for new and interesting products that the user has probably never seen before. The metaverse has the capability to emerge as an innovative venue, particularly in the context of recommendations generated to users. This innovation is reflected by the data, which are collected in different forms to enable the generation of more novel recommendations. The novelty factor will enable enhanced experience through the generation of unique recommendations, which in addition to matching the users’ needs will open new choices for them. For instance, product recommendations in the metaverse can consider the real-time interactivity provided by the metaverse, and provide 3D visual effects of the products in addition to tactile sensations, unlike conventional systems that can only display images of the goods or hyperlinks of the results to the user (Wei et al., 2023). Overall, exploiting the capabilities of the metaverse will improve the novelty of recommendations. From studies in the literature that have explored the novelty of the recommendations in conventional e-commerce platforms, it is clear that the degree to which recommendations are novel is a significant factor determining the quality of recommendations produced by recommender systems (Ali Abumalloh et al., 2020). We therefore propose the following two hypotheses:

H1: The capabilities of the metaverse have a positive impact on the novelty of recommendations.
H2: The novelty of recommendations has a positive impact on the quality of recommendations.

Capabilities of the metaverse and the accuracy and quality of RAs

The quality of an RA can be examined in two ways: through a system-centric or a user-centric evaluation (Cremonesi et al., 2013). In a system-centric assessment, researchers are interested in the design of and improvements to the predictive techniques used in the RA, which are used to build a product suggestion list, optimise the performance of the RA, and hence give consumers a more fulfilling experience (Knijnenburg, 2012). However, the predictive accuracy of the recommendation does not necessarily mean a fulfilling user experience, and it is essential to consider the contrast between the recommendations presented to users and the actual users’ choices, since not all suggestions will become user choices (Hazrati & Ricci, 2022). In contrast, the quality of the RA is determined in a user-centric assessment using data gathered from individuals that have engaged with the system via different approaches. The quality of the recommendations determined by system-centric methodologies may produce conflicting findings compared to the results of user-centric metrics of the quality of the suggestions. Scholars have recently stated that the objective of the RA should move beyond making accurate predictions, thus indicating the importance of considering users’ perceptions of the quality of the generated recommendations (Pu et al., 2011). In this research, we will focus on users’ perceptions of the accuracy of recommendations, based on the extent to which consumers believe the presented recommendations are in agreement with their tastes.

The capabilities of the metaverse give rise to innovative approaches towards providing accurate recommendations, which are facilitated through the collection of users’ data from diverse channels, thereby aiding the RA in generating recommendations that accurately match users’ tastes and preferences. The capabilities of the metaverse can facilitate user-centered, conscious experiences by successfully adapting visualisations that meet user requirements, especially in terms of timing, location, and information presentation (Wei et al., 2023). The capabilities of the metaverse can be used to create accurate automated recommendations based on user behavioural data, such as clicks, tracks, and gaze movements (Lee, 2022). Furthermore, through an empirical analysis, the capabilities of the metaverse can enable the arrangement of visual recommendations in a way that does not obstruct the sight of other components of the system (Wei et al., 2023). Users can interact with and control these recommendations directly or through non-player characters. Intelligent robots, for example, may offer guidance, engage with people through visualisation-based interaction, and help users perceive the metaverse world. In addition, previous studies in the context of classical RAs have reported that perceived accuracy impacts the overall quality of the RA (Ali Abumalloh et al., 2020; Nilashi et al., 2016). Accordingly, we propose the following two hypotheses:

H3: The capabilities of the metaverse have a positive impact on the accuracy of recommendations.

H4: The accuracy of recommendations has a positive impact on the quality of recommendations.

Capabilities of the metaverse and the diversity and quality of RAs

To achieve the most effective compromise in terms of the choice between accuracy and diversity, a growing number of researchers have treated the tasks of an RA as an optimisation issue, with accuracy and diversity metrics as conflicting goals (Karabadji et al., 2018). Diversification is a popular topic within research on RAs, as it assists in addressing the issue of overfitting and enhances user experience. A high level of diversity in RAs means that the system makes a variety of product selections that are customised to the user's requirements and choices (De Biasio et al., 2023). To achieve high-quality recommendations, a diverse set of suggestions is essential. However, diversification impacts users differently depending on their personalities: people who are open to trying new things tend to favour a wider range of recommendations. Diversifying recommendations to boost user satisfaction by representing the complete range of consumer preferences is one of the primary objectives of studies on the topic of diversity (Kunaver & Požrl, 2017). RAs that offer a diverse set of recommendations can make users more satisfied in several ways (Beel et al., 2013): firstly, diverse recommendations can introduce users to new products that they might not have discovered on their own; and secondly, a variety of recommendations can prevent users from getting bored with the system (Nilashi et al., 2016). This can increase users' trust by providing them with more options that are aligned with their interests.

The metaverse can help an RA to suggest diverse products and unusual experiences that users might like, as it provides the RA with more information about what users prefer. This information is gathered from user interactions and engagement, and can be used to suggest new and diverse products. Moreover, the metaverse indirectly influences the diversity of recommendations by exposing users to a broader range of experiences, which can shape users' preferences, leading to more diverse product suggestions. Incorporating metaverse capabilities into an RA can therefore result in a richer and more satisfying user experience. Diversity in recommendations can be reflected through the capabilities of the metaverse in the form of diverse sets of products, diverse interaction experiences with the recommendations, and diverse forms of visualisation of recommendations.

In addition, the innovativeness of the metaverse can help to address the problems of data sparsity and cold start, which have been linked to the diversity of recommendations in several studies (Reshma et al., 2016). To overcome these issues, the metaverse provides several forms of data collection that can aid in improving the diversity of recommendations, including dynamic data, cross-experience data, and data collected from avatars representing users (Wei et al., 2023). It is therefore likely that including the capabilities of the metaverse will increase the variety of recommendations in RAs. Building on results in the literature in regard to the impact of diversity on the quality of an RA (Nilashi et al., 2016), we propose the following hypotheses:

H5: The capabilities of the metaverse have a positive impact on the diversity of recommendations.

H6: The diversity of recommendations has a positive impact on the quality of recommendations.

Quality, affective trust, and loyalty

The majority of online retailers now use RAs to help individuals make purchases and to lessen the cognitive strains associated with information overload. However, only a limited number of studies have explored users' loyalty in the setting of e-commerce RAs (Ali Abumalloh et al., 2020; Yoon et al., 2013). Given the fierce competition in the digital world, loyalty or continuing intention has been highlighted as an indicator of the effectiveness of digital venues (Kaur et al., 2020; Tseng et al., 2018). Authors in the literature have explored individuals' interactions with online stores over time using objective metrics that can be measured by the purchase proportion; however, purchase proportion metrics related to loyalty have been critiqued for being only a partial estimation of consumers' commitment (Anderson & Srinivasan, 2003), meaning that it is important to examine the elements that can encourage people to remain loyal to online shopping sites and technologies focusing on different behavioral and attitudinal indicators.

We adopted the cognitive-affective-behaviour model, referred to here as the ABC model, to investigate customers' loyalty toward an RA in the metaverse. This is a basic model that outlines a three-part structure of attitudes, detailing how people evaluate products and services through cognitive, affective, and behavioral components (Eagly & Chaiken, 1998). In the literature, these three components have been explored with a focus on various appraisal, attitudinal, and behavioural factors; for instance, Sandyopasana and Alif (2020) adopted this model to explore the factors of quality (cognition), trust and satisfaction, switching barriers (affective), and loyalty (behavior), whereas another study by Q. Zhang et al. (2023a) explored the perception of value (cognition), satisfaction (affective), and loyalty (behaviour) in the context of mobile payments.

In our model, the quality dimension of an online RA can provoke an affective trust toward the RA, which can lead to loyalty towards the RA. Affective trust is defined as feelings of confidence towards the service provider, which are provoked by the care and concern the service provider extends (Johnson & Grayson, 2005). In this research, loyalty is considered a behavioural construct that is reflected by the intention to use the system again for the purchase process (Abumalloh et al., 2020). Loyalty is also reflected by the intention to react in a positive manner toward online merchants. The behavioural intention towards longstanding engagement with the system is induced by consumers' feelings of confidence (affective trust). Thus, following the ABC framework and building on the extant literature, we present the following hypotheses:

H7: The quality of recommendations has a positive influence on the affective trust in the RA.

H8: Consumers' affective trust has a positive influence on users' loyalty to the RA.

Privacy, recommendations quality, and trust

Although the metaverse offers immense potential advantages, it is imperative to acknowledge that the issues of privacy and security require attention (Fernandez & Hui, 2022), and that concerns have been consistently raised in regard to virtual systems in the literature (Barth et al., 2022; Jeon & Lee, 2022; Lata & Singh, 2022; Schomakers et al., 2021; Soumelidou & Tsohou, 2021). These concerns are more prevalent in the context of the metaverse. In a survey carried out in the United States, a significant proportion of respondents (71 %) reported apprehension over their privacy and security in the metaverse (Statista, 2022b). Moreover, 43 % of all participants harboured major concerns over the potential theft of their real identity in the metaverse. A further substantial proportion (approximately 41 %) held the belief that safeguarding their data within the metaverse would pose formidable difficulties.

Privacy concerns have been explored in the literature with a focus on both their antecedents and consequences, including in the context of the metaverse. Several studies have indicated that privacy concerns in the metaverse stem from the collection and sharing of users' data (Alkaeed et al., 2023; Canbay et al., 2022). The metaverse is subject to several privacy risks, such as insecure design, broken authentication, data injection, phishing, unauthorised access, data theft, eavesdropping, and personal information leakage (Huang et al., 2023). Privacy concerns have been explored in contexts beyond the metaverse in the literature, with a focus on their significant impact on users' behavior across various settings. The authors of (Sheehan & Hoy, 1999) reported that privacy concerns led to more conservative behavior in terms of personal information sharing. In another study (Phelps et al., 2001), privacy concerns were found to impact purchase behaviour and the purchase decision process (catalogue purchasing habits). Anic et al. (2019) also indicated that privacy concerns impacted both the fabrication of personal information and willingness to share information. In a study by Bansal and Zahedi (2008), privacy concerns were found to moderate the relationship between the quality of privacy statements and trust. In this study, people with high levels of privacy concerns were found to rely on the adequacy of the privacy policy statement. In our research, we aim to explore how privacy concerns moderate the relationship between RA quality and customer trust. Hence, we hypothesise that perceived privacy has a moderating impact on the relationship between the recommendation quality and customer trust:

H9: Perceived privacy has a moderating impact on the relationship between the quality of recommendations and customer affective trust.

Product knowledge, trust, and loyalty

In the realm of online commerce, goods are frequently categorised into two main types: search items, which are distinguished by the ability to verify their attributes before purchase, and experience items, where the focus is on the experiential aspect, which can only be evaluated after purchase (Yoon et al., 2013). Goods classified as 'searchable' are those that offer comparatively straightforward ways to verify and review their attributes prior to completing a purchase; in contrast, the characteristics of experiential items cannot be examined or verified easily before they are consumed. Movies often serve as prime examples of experiential goods. Numerous studies have found that consumers are more likely to heed the advice of RAs for experience items than for search items, as the evaluation of experience items is more complex than for search items (Aggarwal & Vaidyanathan, 2003). The user's experience and knowledge of the product are important when evaluating different attributes of recommendations, particularly for experiential goods or services.

In their research, Xiao and Benbasat (2007) discovered that users with higher product expertise tended to have less favorable evaluations of a CF RA. Perera (2000) explored the interaction effects between different types of RAs (CBF versus CF) and users' knowledge about product classes. The findings revealed that customers with less knowledge of the products had more positive affective reactions, such as satisfaction and affective trust, towards CF RAs compared to CBF RAs. Customers' level of knowledge about the product can also influence their perceptions of the recommendation, since experienced consumers may rely less on RA recommendations due to their extensive knowledge of the product. However, this may not be the case in the context of the metaverse, as advanced algorithms and artificial intelligence approaches are frequently used to offer consumers tailored recommendations, based on information collected from users. Hence, customers are given recommendations that are more accurate and in line with their preferences and needs when they have a better level of product knowledge.

Previous studies have explored the relationships between product knowledge, quality, satisfaction, trust, and loyalty in traditional e-commerce. For instance, product knowledge was found to have a moderating impact on the relationship between recommendation quality and satisfaction in a study by Yoon et al. (2013), and on the relationship between restaurant stimuli (e.g., quality) and diners' emotions in a study by Peng and Chen (2015). In our study, we aim to examine the impact of product knowledge on the relationship between trust and loyalty. Based on the above discussion, we hypothesise that:

H10: Product knowledge has a moderating impact on the relationship between affective trust and customer loyalty.

Based on the above discussion, and the proposed hypotheses, we present the initial research model in Fig. 1.

Method of the study

Data collection

In this study, we targeted participants in Malaysia through several modes, including WhatsApp, LinkedIn, and Facebook. At the beginning of the survey, participants were provided with the following link: https://www.youtube.com/watch?v=0OtIM0L7lLo. The questionnaire includes three main parts: the first part consists of two screening questions, the second part contains demographic data, and the third part includes the main survey items. Those who did not meet the screening criteria were excluded from the survey. To ensure data completeness, all survey questions were set as required for completion. Referring to the sample size, we followed the 10 times rule of thumb by Barclay et al. (1995), which suggests that the sample size should be at least 10 times the larger of: (1) the highest number of formative indicators used to measure a single construct, or (2) the highest number of structural paths directed at a particular construct in the structural model. This rule of thumb effectively means that the minimum sample size should be 10 times the maximum number of arrowheads pointing at a latent variable in the PLS path model. Participants were asked to indicate their level of familiarity with recommender agents and their knowledge of using the metaverse in the retail industry. Responses from participants who indicated they were not at all familiar with either of these topics were excluded from the study. The main survey comprises nine sections designed to measure research hypotheses. Each item in the survey is assessed using a 5-point Likert scale (see Appendix A). The survey items allow participants to express their attitudes toward the variables subjectively. The data collection process spanned approximately four months, from January 2023 to April 2023. We received 288 valid responses, which were used for analysis. The demographic data analysis is presented in Table 1. As shown in Table 1, the majority of respondents were male, with the most common age range being 36–40. Most participants reported an average income of \$751–\$1500. Additionally, most respondents were moderately familiar with both the recommender system and the use of the metaverse.

Empirical results

We used SmartPLS to conduct analyses on both the structural and measurement models to ensure the validity and reliability of our research model. We adopted a structured approach to evaluate the quality of the collected data and the significance of the hypotheses using PLS-SEM. This method is robust, as it can handle complex models involving multiple constructs, indicators, and layers of relationships, making it well-suited for the context of our study (Hair Jr et al., 2020). It can also handle both reflective and formative measurement models. Structural Equation Modeling (SEM) is used to assess the relationships between independent and dependent variables (Hair et al., 2013). The quantitative research community recognizes SEM as a reliable method for factor analysis and path analysis. To ensure the survey yielded

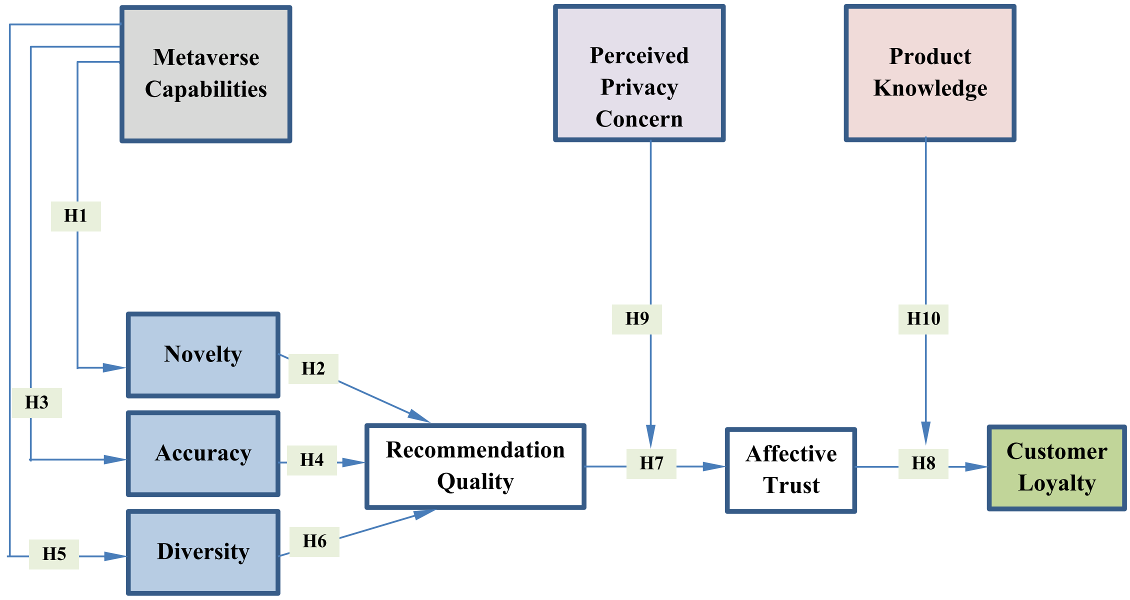

Fig. 1. Initial research model.

accurate and valid results, we conducted three main checks on the outer model using the tool: Convergent Validity (CV), Internal Consistency (IC), and Discriminant Validity (DV). For the CV test, all survey indicators exhibited outer loadings above 0.4. Hence, following the guideline set by Hair et al. (2013), we decided to retain all items for further analysis. The next step in evaluating Convergent Validity (CV) involves the average variance extracted (AVE). The AVE test requires that the correlation between items within the same factor must meet a minimum threshold of 0.5. All factors in the proposed model satisfied this AVE criterion. To assess Internal Consistency (IC) of the outer model, both Composite Reliability (CR) and Cronbach's Alpha (CA) tests were employed. Each factor in the study model needed to achieve a minimum threshold of 0.7 for both tests. The analysis confirmed that the IC of the outer model was supported (see Table 2).

Several tests were conducted to assess the Discriminant Validity (DV) of the model: the Heterotrait-Monotrait Ratio of Correlations

Table 1
Demographic results of the participants.

Item		N = 288	
		Frequency	Percent
Gender	Female	69	24.0
	Male	219	76.0
Age	Under 30	9	3.1
	30 – 35	52	18.1
	36 – 40	81	28.1
	41 – 45	64	22.2
	46 –50	63	21.9
	51 and over	19	6.6
Income	0–500$	21	7.29
	$501 - $750	94	32.64
	$751–$1500	113	39.24
	$1501-$2000	31	10.76
	Above 2000	29	10.07
Favorite E-Commerce Website	Alibaba	4	1.4
	Amazon	46	16.0
	eBay	3	1.0
	Lazada	62	21.5
	Mudah.my	36	12.5
	Namshi	4	1.4
	Shein	4	1.4
	Shopee	27	9.4
	Taobao	66	22.9
	Other	36	12.5
Level of Familiarity with the Recommender System	High Familiarity	117	40.63
	Moderate Familiarity	157	54.51
	Low Familiarity	14	4.86
Level of Familiarity with the Usage of the Metaverse in the Retail Industry	High Familiarity	125	43.4
	Moderate Familiarity	147	51.04
	Low Familiarity	16	5.56

Table 2
Constructs reliability and validity.

Item	Outer loadings	Cronbach's Alpha	Composite Reliability	AVE
Accuracy		0.722	0.825	0.550
ACC1	0.641			
ACC2	0.548			
ACC3	0.856			
ACC4	0.869			
Customer Loyalty		0.820	0.893	0.735
CL1	0.872			
CL2	0.824			
CL3	0.875			
Diversity		0.731	0.882	0.788
DIV1	0.888			
DIV2	0.888			
Novelty		0.785	0.903	0.823
NOV1	0.898			
NOV2	0.916			
Perceived Privacy		0.826	0.884	0.657
PPV1	0.783			
PPV2	0.807			
PPV3	0.836			
PPV4	0.816			
Product Knowledge		0.719	0.840	0.637
PRK1	0.834			
PRK2	0.800			
PRK3	0.758			
Recommendation Quality		0.844	0.895	0.681
RECQ1	0.844			
RECQ2	0.797			
RECQ3	0.847			
RECQ4	0.811			
Trust		0.890	0.948	0.900
TRU1	0.954			
TRU2	0.944			
Metaverse Capabilities		0.722	0.844	0.643
MC1	0.810			
MC2	0.832			
MC3	0.763			

Table 3
Heterotrait-monotrait ratio (HTMT).

Construct	ACC	CL	TRU	DIV	NOV	PPV	PPV	RECQ	MC
Accuracy									
Customer Loyalty	0.771								
Customer Trust	0.716	0.742							
Diversity	0.669	0.850	0.751						
Novelty	0.687	0.735	0.605	0.769					
Perceived Privacy	0.880	0.876	0.760	0.838	0.807				
Product Knowledge	0.840	0.568	0.409	0.562	0.576	0.601			
Recommendation Quality	0.709	0.742	0.693	0.735	0.695	0.803	0.461		
Metaverse Capabilities	0.867	0.605	0.563	0.458	0.520	0.685	0.579	0.557	

Table 4
Fornell-Larcker criterion.

Construct	ACC	CL	TRU	DIV	NOV	PPV	PPV	RECQ	MC
Accuracy	0.742								
Customer Loyalty	0.604	0.857							
Customer Trust	0.579	0.636	0.949						
Diversity	0.482	0.659	0.607	0.888					
Novelty	0.517	0.595	0.513	0.585	0.907				
Perceived Privacy	0.702	0.724	0.655	0.652	0.655	0.811			
Product Knowledge	0.597	0.447	0.334	0.415	0.439	0.477	0.798		
Recommendation Quality	0.577	0.617	0.609	0.581	0.573	0.673	0.370	0.825	
Metaverse Capabilities	0.650	0.467	0.452	0.333	0.389	0.529	0.423	0.437	0.802

(HTMT), the Fornell-Larcker (FL) criterion, and Cross Loadings (CL). The DV test evaluates the degree of differentiation between research factors. The HTMT criterion measures the average correlations between indicators across different constructs. The FL test ensures that the correlation between each factor and other factors in the model is less than the square root of the AVE for that factor. The CL test requires that the outer loadings of indicators for each factor be greater than their cross-loadings. The results of the DV tests are detailed in Tables 3, 4–5.

In the next stage, the relationships between research variables were examined. Evaluating the research model involves testing the proposed hypotheses using path coefficient analysis, which is a crucial step. Additional tests for the inner model include examining coefficients of determination and effect size. The final inner model is presented in Figs. 2 and 3, and Tables 6 and 7. To assess the model's paths, a bootstrapping procedure was conducted (Hair et al., 2013). The results confirm the significance of all research hypotheses within the model. Analysis of the inner model showed that the impact of metaverse capabilities on the accuracy of RAs is the strongest among the research paths, with a coefficient of 0.650. This is followed by the influence of trust on user loyalty, which has a coefficient of 0.552. The model's predictive accuracy was assessed using the R-squared test, which evaluates the proportion of variance in the endogenous variable explained by the exogenous variables (Hair et al., 2013). R-squared values range from 0 to 1, with higher values indicating greater predictive accuracy. In this study, R-squared values range from 0.111 to 0.492. Given that the research focuses on consumer-oriented topics, specifically on understanding trust and loyalty among consumers, an R-squared value of 0.2 is considered significant (Hair et al., 2013).

The results indicate that the accuracy, novelty, and diversity of RAs account for 48.8 % of the variance in recommendation quality. Additionally, the research model explains 46.7 % of the variance in user loyalty. Furthermore, the model accounts for 49.2 % of the variance in users' trust.

The moderation effect indicates that the presence of a third variable can either strengthen or weaken the relationship between an endogenous factor and an exogenous factor (Hair et al., 2013). This study primarily investigates how perceived privacy affects the relationship between RA quality and trust. Our goal is to determine the significance of the moderator's impact on this relationship. To achieve this, we employed a two-stage approach to operationalize the interaction effect using SmartPLS (Hair et al., 2013). The analysis results (Fig. 4) revealed that perceived privacy moderates the relationship between RA quality and consumer trust. Specifically, a higher level of perceived privacy is associated with a stronger positive relationship between recommendation quality and customer trust, as indicated by a significant beta coefficient of 0.092. Conversely, the moderation effect of product knowledge on the relationship between trust and loyalty was not supported.

Table 5
Cross loadings results.

Items	ACC	CL	DIV	MC	NOV	PPV	PRK	RECQ	TRU
ACC1	0.641	0.357	0.314	0.381	0.330	0.345	0.567	0.300	0.354
ACC2	0.548	0.354	0.324	0.296	0.336	0.400	0.319	0.306	0.349
ACC3	0.869	0.526	0.411	0.584	0.429	0.665	0.477	0.537	0.508
ACC4	0.856	0.523	0.385	0.592	0.436	0.601	0.445	0.508	0.484
CL1	0.574	0.872	0.582	0.423	0.565	0.640	0.433	0.550	0.583
CL2	0.461	0.824	0.529	0.353	0.422	0.621	0.345	0.518	0.520
CL3	0.510	0.875	0.581	0.422	0.534	0.600	0.365	0.517	0.528
DIV1	0.422	0.577	0.888	0.281	0.520	0.545	0.331	0.524	0.551
DIV2	0.434	0.592	0.888	0.309	0.518	0.613	0.405	0.508	0.527
MC1	0.568	0.405	0.262	0.810	0.299	0.420	0.384	0.341	0.332
MC2	0.534	0.351	0.273	0.832	0.309	0.413	0.299	0.392	0.411
MC3	0.456	0.368	0.266	0.763	0.330	0.441	0.334	0.317	0.344
NOV1	0.448	0.498	0.484	0.379	0.898	0.529	0.368	0.464	0.371
NOV2	0.488	0.577	0.573	0.329	0.916	0.654	0.426	0.571	0.551
PPV1	0.703	0.608	0.495	0.519	0.519	0.783	0.414	0.560	0.548
PPV2	0.585	0.602	0.502	0.484	0.552	0.807	0.415	0.485	0.515
PPV3	0.501	0.625	0.583	0.372	0.575	0.836	0.361	0.601	0.561
PPV4	0.478	0.504	0.532	0.335	0.471	0.816	0.354	0.531	0.492
PRK1	0.497	0.327	0.298	0.348	0.341	0.346	0.834	0.258	0.241
PRK2	0.514	0.415	0.384	0.370	0.383	0.473	0.800	0.351	0.312
PRK3	0.406	0.310	0.296	0.284	0.318	0.293	0.758	0.261	0.234
RECQ1	0.505	0.499	0.465	0.397	0.511	0.598	0.345	0.844	0.493
RECQ2	0.402	0.511	0.417	0.319	0.405	0.528	0.236	0.797	0.399
RECQ3	0.498	0.534	0.527	0.373	0.449	0.569	0.340	0.847	0.522
RECQ4	0.487	0.496	0.498	0.349	0.515	0.528	0.290	0.811	0.573
TRU1	0.563	0.623	0.599	0.443	0.535	0.655	0.337	0.607	0.954
TRU2	0.535	0.582	0.550	0.413	0.434	0.585	0.296	0.546	0.944

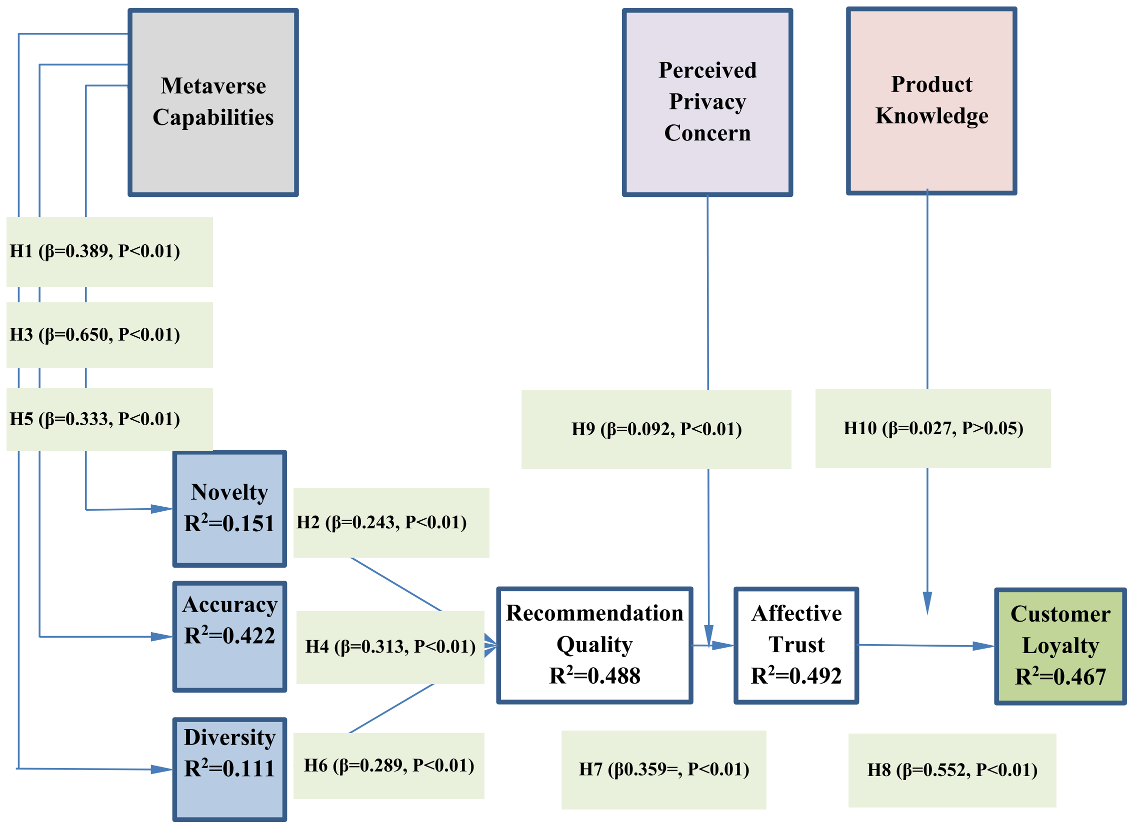

Fig. 2. Inner model analysis.

The results of the model fit

The summary of the results shows that:

i. Metaverse capabilities significantly affect recommendation novelty, recommendation accuracy, and recommendation diversity, with β values of 0.389, 0.650, and 0.333, respectively.
ii. Recommendation novelty significantly impacts recommendation quality, with a β value of 0.243.
iii. Recommendation accuracy has a significant effect on recommendation quality, with a β value of 0.313.
iv. Recommendation diversity significantly influences recommendation quality, with a β value of 0.289.
v. The quality of recommendations positively affects affective trust in recommendations, with a β value of 0.359.
vi. Perceived privacy enhances the positive relationship between recommendation quality and affective trust, with a β value of 0.092.

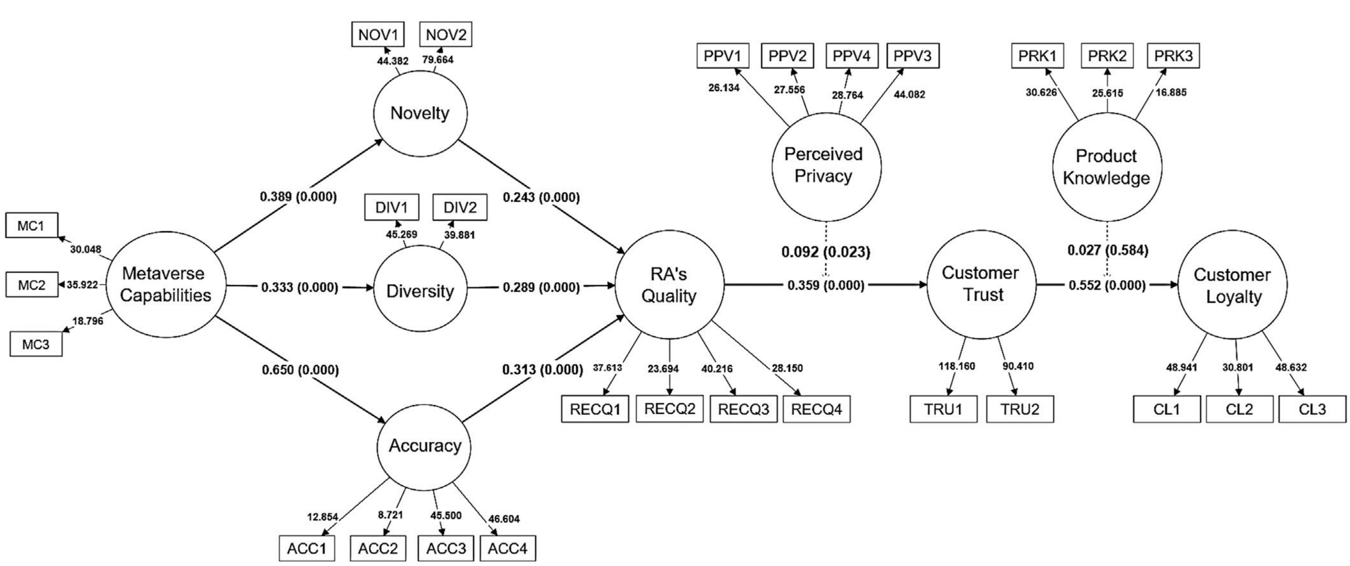

Fig. 3. Inner model analysis (SmartPLS).

Table 6
Path coefficient results.

	Hypotheses	β	T Values	P Values	F^2	Status
H1	Metaverse Capabilities -> Novelty	0.389	7.276	0	0.178	Supported**
H2	Novelty -> Recommendation Quality	0.243	3.497	0	0.068	Supported**
H3	Metaverse Capabilities-> Accuracy	0.650	17.666	0	0.731	Supported**
H4	Accuracy -> Recommendation Quality	0.313	4.23	0	0.130	Supported**
H5	Metaverse Capabilities -> Diversity	0.333	5.863	0	0.124	Supported**
H6	Diversity -> Recommendation Quality	0.289	4.881	0	0.100	Supported**
H7	Recommendation Quality -> Customer Trust	0.359	4.865	0	0.123	Supported**
H8	Customer Trust -> Customer Loyalty	0.552	12.164	0	0.499	Supported**
H9	Perceived Privacy x Recommendation Quality -> Customer Trust	0.092	2.268	0.023	0.023	Supported*
H10	Product Knowledge x Customer Trust -> Customer Loyalty	0.027	0.547	0.584	0.002	Not Supported
Perceived Privacy -> Customer Trust		0.434	6.014	0	0.201	Supported**
Product Knowledge -> Customer Loyalty		0.263	4.673	0	0.115	Supported**

Significant at P** < 0.01, P*< 0.05 and Not Significant (NS) at P≥0.05,

Table 7
R-Squares results.

Factor	R-square	R-square adjusted
Accuracy	0.422	0.420
Customer Loyalty	0.467	0.462
Customer Trust	0.492	0.486
Diversity	0.111	0.107
Novelty	0.151	0.148
Recommendation Quality	0.488	0.482

vii. Affective trust significantly influences users' loyalty, with a β value of 0.552.

Discussion

RAs have been implemented in the majority of classical online venues to reduce intellectual effort, which is linked to the issue of information overload, and to help individuals to select the right option, product, or service (Nilashi et al., 2016). RAs are also decision support tools that can help an individual to make the best judgment, as choice models are implemented in these systems to support individuals in their selections (Xiao & Benbasat, 2007). In the literature, both attitudinal and behavioral metrics have been used to assess the experiences of individuals while interacting with RAs. Several approaches have been used to appraise individual experiences, including online surveys (Pu et al., 2011) and controlled experiments (Knijnenburg et al., 2012). The results of our study build on the existing literature, with the aim of exploring users' perceptions towards the RAs in the emerging and novel context of the metaverse.

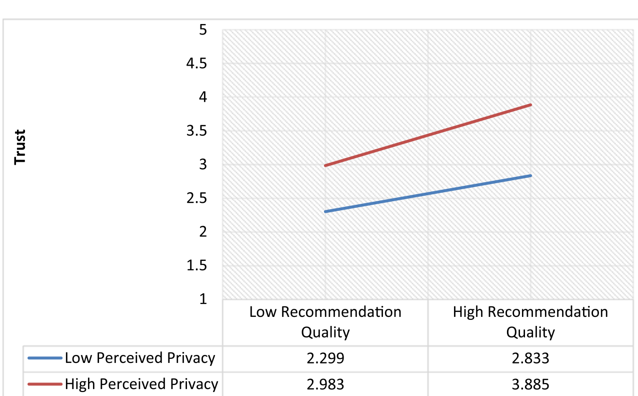

Fig. 4. Structural model (variance-based technique).

The connection between the RA and the individual has been described as an agency-individual connection, where maintaining a level of confidence in the integrity of the RA is essential to conquering the individual's worries (Benbasat & Wang, 2005). The influence of trust on the individual's attitudes and activities has been widely discussed in previous studies, as trust plays a crucial role in mitigating perceived risks and fostering enduring relationships with an electronic medium or tool (Asiamah et al., 2016; Lenzini et al., 2010). Trust in an RA can be developed by presenting the individual with high-level choices (Ali Abumalloh et al., 2020). From the individual's perspective, to build confidence in RA services, the system should offer a selection of options that align with the user's interests (Nilashi et al., 2016; O'Donovan & Smyth, 2005). Trust has also been explored previously as an enabler of diverse outcomes, including attitude (Arpaci, 2016), satisfaction (Kim et al., 2009), loyalty (Ali Abumalloh et al., 2020; Lin & Wang, 2006), participation (Corbitt et al., 2003), purchase intention (Kim et al., 2008), and word-of-mouth intention. However, trust in RAs has not been investigated in the context of the emerging capabilities offered by the metaverse.

Integration of the recommender system within the metaverse is important to overcome the problem of cognitive overload. Users of the metaverse are subject to numerous forms of interactions, and will be presented with different types of data, which can overwhelm their cognitive abilities (Wei et al., 2023). In this context, recommender systems can aid users in reaching decisions. The importance of this study lies in exploring how to exploit the innovative capabilities of the metaverse to generate high-quality recommendations in order to gain the user's trust.

The findings of our study showed how the capabilities of the metaverse affect the quality factors of an RA, such as novelty, diversity, and accuracy, in a setting that has not previously been covered in the literature. The novelty, diversity, and accuracy of an RA are impacted by the metaverse's innovative capabilities in a number of ways. The metaverse can enhance RAs due to its participative and immersive qualities. Firstly, the incorporation of a wider spectrum of information and data sources in the selection procedure of recommendations is made possible by using the innovative capabilities of the metaverse. By exploiting the extensive virtual setting and interactive features of the metaverse, RAs can offer users a wider range of products, services, or even experiences. A greater variety of suggestions may enhance the individual's experience and give a better match to his/her tastes. Secondly, the metaverse can facilitate the generation of novel suggestions. Users may learn about uncommon or cutting-edge suggestions due to the metaverse's ability to replicate and create novel virtual experiences. The immersive features of the metaverse encourage users to explore potentially undiscovered items while also generating cutting-edge suggestions that match their tastes. Finally, the capabilities of the metaverse can affect the accuracy of the suggestions. The various data sources and interactive feedback loops of the metaverse can be used to gather complete information on the user's preferences, behaviours, and contextual data. This wealth of data will enhance the accuracy and overall quality of the RA by enabling the algorithms to base their predictions and suggestions on particular user profiles and in-the-moment interactions within the metaverse.

The results of our study supported the hypothesis of a moderating impact of perceived privacy on the relationship between the quality of an RA and the individual's perceptions of trust. Within the context of the metaverse, users are expected to perceive higher levels of risk concerning the privacy of their personal data compared to traditional online commerce. In this regard, RAs play a vital role as a trust object, as users rely on both the recommended products and the process through which selections are generated to establish trust (Benbasat & Wang, 2005; Xiao & Benbasat, 2007). However, limited attention has been paid to users' perceptions of privacy risks in relation to using the metaverse, apart from insights derived from the findings of online surveys, such as that by Statista (2022b). Given the substantial collection of personal data in the metaverse, privacy emerges as a significant concern for both retailers and consumers. Moreover, the metaverse may be susceptible to security threats, necessitating the implementation of robust security measures such as encryption, authentication, and authorisation.

Our results did not support the hypothesis of a moderating impact of product knowledge on the relationship between customer trust and loyalty. This stands in contrast to the results reported by Yoon et al. (2013), who examined how product knowledge and consumers' experience moderated the relationships between (i) the quality of an RA and user satisfaction, and (ii) user satisfaction and user loyalty. They found a moderating influence of product knowledge on the path between the quality of an RA and customer satisfaction. However, their study differed from ours in terms of the context of the study and the relationship in which the moderating impact was explored, as they focused on the impact of the quality of an RA on customer satisfaction.

Conclusions and implications

Theoretical contributions

The theoretical implications of this study can be divided into five main areas. Firstly, we empirically tested the moderating impact of perceived privacy on consumers' trust towards RAs in the context of the metaverse. Establishing trust and credibility with customers is essential for retailers, and privacy plays a pivotal role in achieving this goal. By prioritising and implementing robust privacy measures, retailers can effectively attract customers and foster a sense of trust, thereby enhancing their reputation and credibility in the eyes of their clientele (Belanger et al., 2002; Tsai & Yeh, 2010). Customers want to know that their personal information is secure and that their privacy is respected when they shop in a physical store or online (Huang et al., 2004), and we believe that the metaverse is no exception. In the current digital landscape, customer concerns over the sharing of personal information have intensified due to the prevalence of data breaches and cyberattacks. Retailers who place a strong emphasis on security and privacy are better positioned to attract and retain customers. By implementing robust security measures and adhering to data protection regulations, these businesses can differentiate themselves from competitors that may have less stringent security and privacy practices. The success of metaverse platforms within the retail industry hinges on the platform providers' adeptness in handling security, privacy, and trust-related challenges (Gupta et al., 2023).

Secondly, this study addresses a research gap in the field of RAs by exploring factors that contribute to users' loyalty towards RAs in the emerging and novel realm of the metaverse. Through a review of the existing literature, we were motivated to explore the role of consumers' trust in the relationship between perceived system quality and users' loyalty in the context of metaverse RAs. This hypothesis aligns with previous research conducted in the domain of e-commerce (Hong & Cho, 2011; Hwang & Kim, 2018) and e-commerce RAs (Ali Abumalloh et al., 2020), which highlights the agency relationship between recommender system and users. Recommendations from RAs should be created to meet customers' needs, rather than simply to boost sales for merchants. As a result, the establishment of long-lasting relationships between customers and RAs depends on user trust. Users of online portals turn to RAs for assistance more frequently as their usage and needs in the context of the online market grow. Although RAs can help online shoppers make the best product choices, they are only intended to supplement rather than replace real sellers' recommendations (Benbasat & Wang, 2005).

Thirdly, within the context of e-commerce marketing, loyalty is typically assessed by gathering behavioural data, including purchase rates and purchase sizes. These measures are preferred due to the ease of collection of these data and their ability to provide valuable insights into customer loyalty (Wetsch, 2013). Nevertheless, it is important to note that relying solely on such data can potentially yield misleading measurements of true loyalty (Wetsch, 2013). As a result, researchers have been motivated to investigate subjective measures of users' loyalty toward systems, which is significant in the context of emerging innovation adoption.

Fourthly, our results confirm the three-stage model of the quality-satisfaction-loyalty chain (Oliver, 1999) by considering consumers' perceptions of quality prior to the purchase process and their loyalty, taking into account both rational and emotional factors. Users' attitudes, which are influenced by cognitive and emotive perspectives, are what keep information systems effective. Whereas earlier studies using conventional adoption theories have mostly focused on the cognitive aspect of framing users' attitudes, our study deepens comprehension of this topic by combining both cognitive and affective dimensions of customer experience (Davis et al., 1989). In addition, most prior researchers have investigated users' behaviour in organisational settings, without considering hedonic dimensions (Kim et al., 2005). Since customers seek assistance from RAs for their specific needs, our research differs from other studies in that it considers the individual context of usage, where both utilitarian and hedonic dimensions are significant for consumers' overall evaluations of the system and for consumers' ongoing decisions.

Furthermore, prior research has concentrated on the relationship between trust and IT acceptance, with a focus on the cognitive aspects of trust. However, this study has examined the antecedent and the impact of affective trust on consumers' loyalty. Our research outcomes indicate that affective trust impacts consumers' loyalty, and that affective trust mediates the influence of cognitive beliefs about the quality of the RAs on users' loyalty. As indicated by Komiak and Benbasat (2006), the impact of emotional trust can be increased with higher levels of dependency on the agent. Cognitive beliefs influence affective trust, which in turn helps reduce the uncertainty associated with the evolving capabilities of recommender algorithms in the metaverse, thus alleviating users' concerns.

Finally, in this study, we focused on the medium of virtual retail, adopted an innovative interacting venue (metaverse) as the research object, highlighted the role of cutting-edge technology in enhancing the customer experience, and broadened the related literature in the context of customer behavior and marketing of services. We adopted the cognitive load theory (Brünken et al., 2002) to describe the influence of metaverse recommendation capabilities on users' trust and loyalty. Our research indicates that the capabilities of the metaverse in the shopping arena can affect users' cognitive burden, thereby improving users' emotions regarding a product.

Practical contributions

The practical implications of this study can provide valuable guidance for service providers. Firstly, the immersive and interactive nature of the metaverse will enable the use of data collected through several channels, analysis of the collected data through the innovative capabilities of the metaverse (such as artificial intelligence and machine learning), and the provision of recommendations that meet the needs of users. The quality of these recommendations within the context of the metaverse is anticipated to take a new route: diversity, novelty, and accuracy will be perceived in different ways that go beyond those of classical online commerce portals. All of these aspects add new dimensions to the quality factors that have been explored previously in regard to conventional RA. For instance, in addition to the diversity of product lists, designers should focus on diversifying virtual stores, shopping environments, and product displays. In terms of novelty, the design of a product in 3D will add value to the assessment of novelty. The perception of the accuracy of recommendations can be enhanced in the metaverse. This will be facilitated by the amounts of data collected about users (interactions, preferences, and shopping patterns), which enable the system to provide accurate recommendations that match their interests.

Secondly, service providers should not focus solely on the objective aspects of user experience, as the effectiveness of the system is also influenced by subjective experiences. Subjective experience with the RA also entails hedonic and utilitarian dimensions, both of which exert influence on the user's sustained intention to use the RA in the metaverse. Implicit measures of the system's performance (browsing history, click rate, and purchase history) reflect its objective aspects, and are commonly considered by service providers; however, according to McNee et al. (2006), being accurate by relying on the objective assessment is not sufficient, and there is a need to adopt a user-centric approach to the evaluation of the RA. User-centric evaluation is important in regard to new technology adoption, where users' experiences and the impacts of different factors on such experiences are not fully understood.

Thirdly, experiences in the metaverse provide a range of different views of value, such as sensory (cognitive), emotional, and behavioural components, which are more significant than functional values alone. In particular, we focused on the impact of quality factors (cognitive) on the (affective) dimension of trust, and how trust influenced the (behavioural) dimension represented by loyalty. The findings of our study reaffirm the importance of users' trust in the RAs and its impact on fostering user loyalty, a result that is aligned with those of previous research but within the new and innovative context of metaverse usage. To cultivate users' trust, enhancing the quality of recommendations is essential, as this plays a significant role in shaping users' perceptions.

Fourthly, acknowledging and addressing users' hedonic experiences in the metaverse can contribute to the system's overall appeal and user retention (Frank et al., 2014). Consumers in the metaverse may value experiences more than products when making their decisions, as both emotive and logical folds have an impact on their behaviour (Park & Lim, 2023). In the metaverse, users value the pleasure of the experience itself (Liang et al., 2024). Subjective user perceptions of quality encompass emotional elements that significantly influence user behaviour, and these emotional aspects must be taken into account in the design and implementation of RAs in the metaverse.

Fifthly, the outcomes of this study give rise to the valuable implication that enhancing the quality of an RA can have an influence on improving customer loyalty towards the RA in the metaverse, leading to increased earnings for merchants in a stable manner. This enduring relationship can be further reinforced through an iterative loop between the RA and the customer, where the customer continues to use the system and develops a sense of loyalty towards it. Providing users with the opportunity to express their preferences about items and products to the system can strengthen this relationship and facilitate a more productive user experience. In the metaverse, users' preferences can be reflected in real time, enabling a more enhanced experience (Liang et al., 2024).

Finally, the metaverse blends both actual and virtual environments, allowing users to interact, create, and transact. Although it incorporates several innovations such as AR, VR, and blockchain, extensive interaction with the real world can lead to various types of personal information leakage, posing risks for both customers and retailers (Chen et al., 2024). To foster user trust and encourage widespread adoption, robust security and privacy measures must be implemented, accompanied by transparent communication regarding data collection and usage, as well as user empowerment over personal information. Privacy concerns must be taken into consideration from the beginning of the design process (Di Pietro & Cresci, 2021; Gupta et al., 2023). In particular, control over user data and the prevention of illegal sharing must be carefully ensured in the design and development stages of the retail metaverse (Alkaeed et al., 2023).

Limitations and future research

There are several limitations on the current research. Firstly, the proposed model has a shortcoming in that it only includes three critical variables in relation to the quality of an RA, namely accuracy, diversity, and novelty. Other factors such as transparency, serendipity, attractiveness, and context compatibility could be explored, and their impacts on several desirable outcomes (perceived recommendation quality, trust, satisfaction, and loyalty) could be considered in future research. Transparency of recommendations, for example by presenting explanations to users, can promote users' trust in recommendations (Abumalloh et al., 2020). In addition, the serendipity of recommendations, which is reflected by the levels of surprise and relevance of recommendations, can influence user satisfaction according to Chen et al. (2019). Other factors such as attractiveness and context compatibility have an impact on the quality of a recommendation (Pu et al., 2011). Attractiveness is defined by the level at which the recommendation promotes positive emotions and stimulates users' imaginations, whereas context compatibility refers to the consideration of general or personal contexts by the RAs. These factors have been explored in the context of conventional RA, and the advent of the metaverse RA opens up avenues for future research to explore how these factors influence customers' experiences.

Secondly, the survey was circulated via the web and social media, and it is possible that other modes could improve the number of respondents. The respondents might be considered younger, more tech-savvy, or have specific interests that make them more likely to engage with emerging technologies such as metaverse. Hence, the generalisability of our findings should be considered carefully. Furthermore, our study relied on the responses of participants to a survey, whereas mixed approaches involving interviews and co-designs, for instance, could provide more robustness to the findings and could help in understanding the perceptions of the participants in regard to this emerging technology.

Thirdly, the metaverse can be considered in a variety of contexts. The focus of this study was limited to the retailing context, as the metaverse system will have a significant impact on e-commerce environments. Future studies could focus on the implementation of the metaverse in other areas, such as education, tourism, and gaming.

Finally, the results of our study did not support the hypothesis of a moderating impact of product knowledge on the relationship between trust and loyalty. In order to understand how previous experience and knowledge about the product will influence loyalty, there is a need for more comprehensive research that considers different contexts and product types. As discussed above, the type of product (search vs. experience) can influence the need for detailed information about it before purchasing. The type of product will therefore influence the overall experience with the RA.

CRediT authorship contribution statement

Rabab Ali Abumalloh: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mehrbakhsh Nilashi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Osama Halabi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Raian Ali:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization.

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Appendix A. The questionnaire items

Construct	Item	References
Recommendation Quality	The suggestions presented to me by the metaverse recommendation agent should be helpful. The suggestions presented to me by the metaverse recommendation agent should be relevant. The metaverse recommendation agent should generate the kinds of items I enjoy. The metaverse recommendation agent should generate the kinds of items I prefer.	(Yoon et al., 2013)
Affective Trust	I would feel a sense of personal loss if I were unable to utilize the recommender system services within the metaverse. I feel the metaverse recommender system should respond caringly to my needs in general.	(Ozdemir et al., 2020)
Loyalty	I have a strong inclination to revisit and engage with the metaverse recommendation agent in the future. I highly recommend others make use of the recommender system services provided by the metaverse. I have a steadfast preference for the recommender system of the metaverse that I am not inclined to change willingly.	(Oliver, 1999)
Perceived Privacy	It is important to me that my data in the metaverse will not be subject to any form of misusage. It is important to me that my data in the metaverse will be utilized as intended. It is important to me that I have a full assurance that adequate measures will be taken to protect my data in the metaverse. It is important to me that I do not have concerns regarding the potential misappropriation of my data in the metaverse.	(Dinev et al., 2008)
Diversity	It is significant to me that the metaverse recommended items exhibit notable dissimilarity from one another, ensuring a diverse range of suggestions. It is significant to me that the metaverse recommendations provided to me encompass a wide array of diverse item categories.	(Ali Abumalloh et al., 2020; Nilashi et al., 2016)
Novelty	The novelty of the recommendations presented to me in the metaverse is significant to me. The recommender system in the metaverse should facilitate the exploration and discovery of novel items for me.	(Nilashi et al., 2016; Pu et al., 2011)
Accuracy	The alignment of recommended items with my interests holds considerable importance to me. The provision of valuable suggestions by the recommender holds great significance to me. Ensuring that the recommended items align with my interests is of vital importance to me. The matching of recommended items with my personal interests holds significant value to me.	(Ali Abumalloh et al., 2020)
Metaverse Capabilities	The metaverse capabilities (virtual stores) significantly enhance the shopping experience for customers of retail businesses. The metaverse capabilities (virtual try-on) greatly elevate the shopping experience for customers engaged with retail businesses. Customers engaging with retail businesses can expect a significantly enhanced shopping experience through the utilization of metaverse capabilities.	Developed by the Authors
Product Knowledge	Having access to product information holds significant value to me. Gaining comprehensive product knowledge is of great importance to me. Being well-informed about the details of the product is of utmost importance to me.	(Yoon et al., 2013)

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