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Consumers' Behavioural Intentions to Reuse Recommender Systems: Assessing the Effects of Trust Propensity, Trusting Beliefs and Perceived Usefulness

Nirmal Acharya *, Anne-Marie Sassenberg and Jeffrey Soar

School of Business, University of Southern Queensland, Springfield, QLD 4300, Australia
* Correspondence: nirmal.acharya@usq.edu.au

Abstract: Recommender systems (RSs) are widely utilised across industries as tools to provide users with recommendations based on their preferences. This paper reports on an examination of the influence of trusting beliefs on behavioural intentions to reuse RSs, emphasising the effects of trust propensity, perceived usefulness and product type. A distinctive contribution of this study is the research model, which integrated perceived usefulness as an antecedent of trusting beliefs. Data collected in Australia with 366 participants were used. A new approach (MICOM and PLS-MGA) was performed to assess the moderating effect of product type. The research results indicate that trust propensity has a positive and significant direct effect on consumers' trusting beliefs in an ongoing relationship. The results also suggest that consumers' trusting beliefs and perceived usefulness of RSs positively and significantly affect their intention to reuse RSs. Perceived usefulness of RSs is more important compared to trusting beliefs in predicting consumers' behavioural intention to reuse RSs. Trusting beliefs partially mediate the impact of perceived usefulness on behavioural intentions to reuse RSs. The results also showed an insignificant difference between the effect of different product types on Australian consumers' behavioural intention to reuse RSs. These results have implications for the design of RSs.

Keywords: recommender systems; trust propensity; trusting beliefs; perceived usefulness; product type

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1. Introduction

Continued growth in internet and e-commerce technology accelerates easy access to large amounts of data at any point, and this access has led to a new issue called 'information overload' that can make it time consuming for an individual to find the specific information required [1]. Online merchants commonly use information systems (IS) such as recommender systems to minimise information overload by assisting customers with suggestions that allow them to shop based on their preferences and to avoid the often confusing and excessive advice that can be offered [2–6]. Recommender systems (RSs) not only can reduce search complexity and information overload but also have the ability to enhance decision accuracy [7,8]. RSs are of significant value for the success of an online business. Netflix estimated that 75% of what people watch is generated using recommendations [9]. Their business value was estimated to be over 11.7 billion USD per year and over 1 billion USD per year associated with the recommendations and personalisation the company offers [10].

In contrast to statements extolling the value that RSs contributes to online businesses, several studies have shown that there are negative consequences of applying RSs. Most websites with a recommender system reported low returns on their investments [11]. A prime example is Amazon, which generates approximately 35% of Amazon's sales originated from recommendations by RSs [8,9]. Some of these factors are beyond the objective of prediction precision, but the impact on the consumers' experience (i.e., consumers' subjective assessment for RSs) has resulted in scholars calling for more research in assessing the efficiency of RSs usage [5,12]. Bhattacherjee [13] noted, “the long-term viability of an IS, and its eventual success depends on its continued use”; behavioural intentions to reuse RSs is crucial for the success of RSs [14,15]. There is a pressing need to understand the effects of subjective factors on their behavioural intentions to reuse RSs [9]. Customers must trust RSs and communicate their attitudes, preferences and wants on a continuous basis in order to use and reuse RSs effectively. This research aimed to understand the effects of subjective factors such as trust propensity and trusting beliefs using a trust-centred lens to estimate the consumers’ behavioural intentions to reuse RSs.

Trust, in the IS literature, is referred to as a set of trusting beliefs [16,17] and is a vital subjective factor that is conceptualised as a multi-dimensional construct that comprises cognitive trust and emotional trust [18]. Cognitive trust refers to a trustee’s competence, benevolence and integrity [19,20], and emotional trust explains how secure and comfortable a person feels when depending on the trustee [18]. Although emotional trust is an important dimension of trust [21,22], few studies on RSs in IS literature have investigated the effect of emotional trust [22,23]. There is little empirical evidence detailing how cognitive trust and emotional trust as a component of a comprehensive framework contribute towards behavioural intentions to reuse RSs.

An important antecedent of trusting beliefs is trust propensity (TP) [24,25]. Trust propensity affects both an initial relationship and the effectiveness of an ongoing relationship between the RSs and consumers [26]. Previous studies found trust propensity positively influenced a consumer’s trusting beliefs in online shopping [27,28]. It was also observed that trust propensity was significant throughout the trust process [26,29]. Given the importance of trust propensity, it may seem surprising that its influence on the consumers’ trusting beliefs in an ongoing relationship with recommender systems is still unknown in the literature. Addressing this unknown in the literature is one of the objectives of this study.

Existing literature has indicated that product type affects consumer buying choices [5]. Researchers have shown that, especially in the context of recommender systems, consumer behaviour varies with product type (search vs. experience) [13,23,30]. This research further validates the existing knowledge and get a broader picture of the effect of product type on the customer’s behavioural intention to reuse RSs.

Trust-centred studies have largely avoided improving the design of RSs; instead, they have focused on improving the privacy policy, security, statistic efficiency and reputation of RSs [31]. In the research reported on in this paper, the aim was to fill the gap and explore the influence of consumers’ trusting beliefs on their behavioural intention to reuse RSs, emphasising the design of RSs. In particular, the effects of trust propensity, perceived usefulness, and product type was investigated in an ongoing relationship between RSs and consumers’ behavioural intentions. These may contribute to the design of a trusted recommender system for ongoing relationships. To achieve this goal, the present study equipped a trust centred lens and started from the exploitation of the ResQue Model [32]. The research model of the study used perceived usefulness as an antecedent of trusting beliefs and validated it empirically by using recent approaches (MICOM and PLS-MGA) via a cross-sectional survey involving Amazon customers from Australia. This study also uses the PLSpredict technique to determine whether the inclusion of emotional trust improves the prediction accuracy of consumers’ behavioural intentions.

The paper is organised as follows: the next section discusses the salient literature; based on this, a research model has been created to be empirically examined in the research. Following this is the research method adopted for the study. The findings of the study and discussion are presented in the methodology and ad hoc analysis sections, respectively. The paper concludes with the implications, recommendations for further research and conclusions.

2. Theoretical Background

2.1. Recommender Systems

Recommender systems (RSs) can be expressed as an information processing technology that generates a personalised item recommendation that may interest the target consumer, predict ratings or rank items (including services, products, movies), or both [33]. RSs tries to persuade a user to follow its recommendation. These recommendations have been utilised in various settings, from accounting (e.g., [34]) and finance (e.g., [35]) to e-commerce (e.g., [22]). Prior literature in IS research has proposed the use of recommender systems as a feasible solution for online merchants to tackle data sparsity and scalability and provide personalised item recommendations that alter consumer buying behaviour [30,36–38]. Such systems also play an essential role in the decision-making process, assisting consumers in reducing risks [15] and maximising profitability [39] by enhancing the sales efficiency, making it valuable for both customers and online merchants.

Different kinds of recommendation systems have been developed based on various filtering approaches to try to improve website sales efficiency. In general, recommender systems are classified into different categories based on the filtering method: content-based filtering, context-aware, collaborative filtering, hybrid filtering and random [40–42]. Customers' trust and purchasing decisions can be influenced by recommendation systems (RSs) using a variety of filtering techniques, suggestion diversity, and recommendation accuracy [42]. In terms of trust (i.e., perceptions of competence, compassion, and honesty), Gorgoglione et al. [43] found that the context-aware RSs outperformed the content-aware RSs and the one that provides random recommendations. Based on the assumption that context improves accuracy as well as diversity, and that trust is affected by both of these factors, the experiment should also hold true for collaborative filtering algorithms [42].

The collaborative filtering approaches are recognised as a popular model, among all the recommendation models, because of its major benefits such as domain independency and requirement of minimum rating information for prediction [41]. Collaborative filtering is similar to word-of-mouth recommendations and tracks the behaviour of consumers that are like-minded to provide suggestions to one particular customer [15,44]. These suggestions arise from the statistical analysis of patterns either from data on product ratings specifically provided by other customers or from the implicit monitoring of other customers' purchasing activity by the recommendation system [45]. For example, a collaborative filtering recommendation algorithm offers a list of items for customers because the products have been bought or liked by like-minded customers. A group of customers with identical tastes is referred to as like-minded customers [15]. Collaborative filtering approaches have been applied by many online merchants [46]. The research reported in this paper focuses on recommender systems that use collaborative filtering method to elicit the user's preferences or interests both implicitly and explicitly and recommends tailored products or services accordingly. Due to the complexity of recommendation algorithms, it can be difficult to explain to end-users the rationale behind recommendations [47]. It could lead to trust issues when recommendations fail.

Although the deployment of RSs addresses the key issue of protecting customers from being overloaded with irrelevant and uninteresting information in e-commerce, a critical but often ignored question is whether consumers continue to use RSs after their initial adoption [48]. Several scholars have claimed that the success and long-term viability of a technology are dependent on its ability to be reused or to be used continuously [13,15,49]. Correspondingly, customers must trust RSs and communicate their attitudes, preferences and wants on a continuous basis in order to use and reuse RSs effectively.

2.2. Trust

Trust can be defined as "a willingness to rely on an exchange partner in whom one has confidence" [50]. Previous studies have stressed that online trust in e-commerce is important as it can make positive leverage e-commerce transactions, lower the amount of perceived risk and increase intention to purchase [51]. In RSs studies, trust has been extensively studied using both user- and system-centric evaluation approaches [32,52–54]. Pu et al. [32] presented a balanced measurement framework for evaluating RSs in accord with the technology acceptance model, which they referred to as ResQue (recommender system's quality of user experience). They validated the framework consisting of four layers of high-level construct based on the following influence paths: perceived quality → user beliefs → user attitudes → behavioural intentions. Knijnenburg et al. [53] presented a study that adopted an evaluation framework for RSs. Using a user-centric evaluation approach, the framework extended beyond focusing on the algorithm's accuracy to examine the quality of RSs on an objective and subjective level. Users' experiences were analysed using an abstract method that focused on general user experience concepts. In their study subjective system features and experience factors were shown to be critical in understanding and characterizing users' perceptions of RSs. Abumalloh et al. [52] argued that trust in the RSs is an important mediating factor that can increase customer loyalty towards RSs. Nilashi et al. [54] investigated the characteristics that increase user trust in the recommender system on commercial websites such as Amazon and Lazada. Their work indicated the importance of several trust-building factors (such as website quality, recommendation quality and transparency) on the level of adoption of the recommendations. Though the frameworks presented in these studies provide a solid foundation for evaluating user experiences with RSs. A major drawback in these frameworks is the omission of the cognitive and emotional elements of trust as an indicator of behavioural intentions, which could impede our ability to comprehend customer behaviour [22,55]. Using a thorough framework of trusting beliefs, and a robust statistical analysis technique, is required to answer more specific research questions.

Researchers in the information system studies have used the theory of reasoned action (TRA) [56] to develop a web-based trust model which categorises trust into three categories: (1) trusting beliefs, (2) trusting intentions and (3) trust propensity [19,51,57–59]. Trust in technology (such as recommender systems) is believed to be based on the dimensions of trusting beliefs [31]. This study, therefore, applies the concept of trusting beliefs to determine the impact of trust on shoppers' behavioural intentions to reuse RSs.

2.2.1. Trusting Beliefs

Much of the trust literature in IS conceptualises trust as trusting beliefs (TB); research findings have indicated that people trust technology in the same way they trust other people [16,17]. Since RSs offers interactive functions and personalises advice, like a real person, it can affect shoppers' attitudes and buying intentions [60].

In the context of RSs, Komiak & Benbasat [18] proposed a model in which they conceptualised that trusting beliefs comprise cognitive trust and emotional trust. The cognitive trust consists of three dimensions, related yet distinct: benevolence, integrity, and competence [17,19,57,61]. Prior literature in IS focused primarily on the cognitive dimension of trust and indicated that cognitive trusting beliefs consist of benevolence, competence and integrity [17,19,31,57]. Benevolence, integrity, and competence are defined as follows:

- Benevolence is defined as "the belief that a trustee cares about a trustor and is motivated to act in the trustor's interest" [62].
- Integrity is defined as "the belief that a trustee makes good faith agreements, tells the truth, and fulfils promises" [62].
- Competence is defined as "the belief that a trustee has the ability or power to do for a trustor what the trustor needs to be done" [62].

Wang and Benbasat [17] tested an integrated Trust-TAM model and reported on the effects of consumers' initial evaluation of trust, considering only the cognitive dimension of trusting beliefs, on the intention to adopt the RSs. The study found that the consumers' initial evaluation of trust affected the perceived usefulness of RSs and intention to adopt the RSs. Xu et al. [63] investigated the effect of the cognitive dimension of trusting beliefs on satisfaction and purchase behaviour. Human relationships with RSs rarely address emotional trust, even though emotions are well-known to have a large impact on trusting behaviours [64].

Emotional trust can be defined as how secure and comfortable a person feels when depending on the trustee [18]. It allows a person to go beyond the evidence to ensure that they can rely on the trustee [22]. In online environments, trust is assessed emotionally, and if the level of emotional trust is strong, consumers are more likely to engage in certain behaviours enthusiastically [18,55]. Understanding customers' behaviour may be hindered if we ignore their emotional trust [22,55]. In determining consumers' RSs adoption intention, emotional trust played a vital role beyond cognitive trust [22]. The conceptualisation of trusting beliefs proposed by Ashraf et al. [23] included the emotional trust dimension and still found that trusting beliefs significantly affected buying intention based on RSs.

Table 1 shows a summary of studies that focus on the concept of trusting beliefs, trust propensity, buying behaviours, buying intentions and use intentions. Although trust-related issues in the field of e-commerce and human–computer interaction have been explored widely, research on the contribution of multiple dimensions of trusting beliefs has lacked sufficient study (see Table 1).

Table 1. RSs Studies focusing on the concept of "Trust" and its impact on buying behaviour, buying intention or use/reuse intention.

Study	Independent Variables					Dependent Variables		
	Trusting Beliefs				Trust Propensity	Buying Behaviour	Intention	
	Cognitive Trust			ET			Buy	Use/Reuse
	CT	BT	IT					
[15]	✓	✓	✓				✓	✓
[17]	✓	✓	✓					✓
[22]	✓		✓	✓				✓
[23]	✓	✓	✓	✓			✓	
[31]	✓		✓		✓			✓
[63]	✓	✓	✓			✓		
This Study	✓	✓	✓	✓	✓			✓

Note: CT = Competence Trust, BT = Benevolence Trust, IT = Integrity Trust, and ET = Emotional Trust.

Looking at the independent variables, it is apparent that earlier attempts of trust-centred studies have ignored essential factors such as emotional trust and trust propensity. In most of these studies, initial evaluation of trust has been focused on the space, where consumers first confront certain websites to form a certain degree of trust [65]. This trust may, however, differ from that of existing consumers, who over the years have established trust with the e-vendor. Consumers' behavioural intentions might be based on rational evaluation (cognitive trust), emotional evaluation (emotional trust) or a combination of both [22,66]. An individual's rational evaluation emphasises cognitive assessments of risks and benefits, whereas emotional evaluation focuses on faith and feelings, which can be rational or irrational in nature [66]. To provide more evidence and get a broader picture, the research reported in this paper treats trusting beliefs as a comprehensive framework proposed in a previous study by Ashraf et al. [23] that comprises cognitive and emotional trust.

2.2.2. Trust Propensity

Trust Propensity (TP) is an important antecedent of trusting beliefs. It is the degree to which a person is willing to rely upon others [67]. People differ in their tendency to trust others, regardless of whether the other is a person or system. Prior trust research suggests that trust propensity should be significantly related to TB's dimensions [24,25]. Trust propensity has been incorporated as a control variable in past studies [25,31]. Wang and Benbasat [25] reported that trust propensity significantly and positively affects competence belief. Individual trust propensity is a critical element that may determine consumers' trust. McKnight and Chervany [67] have indicated that consumers' trust propensity would affect their trusting beliefs. Likewise, researchers have shown that trust propensity affects the level of an individual's trust in online shopping [27,28,68]. Trust propensity has an important role in determining online trusting beliefs as it is affected by an individual's past experience [68].

Past studies have consistently demonstrated trust propensity as an important factor in an initial evaluation of trust, but it becomes less important over time in later evaluations [69,70]. Alarcon et al. [69] examined the impact of trust propensity on perceived trustworthiness over time. They ascertained that trust propensity was linked to trustworthiness only in unfamiliar conditions but had no effect over time. Jones and Shah [70] found that trust propensity was initially dominant for trust, but the influence decreased over time while the trustee became dominant. Although research indicates the significance of trust propensity throughout the trust process [26,29], scant research has been conducted to explore its effect in later evaluations. Colquitt et al. [29] found that trust propensity substantially impacted the trustworthiness dimension on both initial and later evaluations. Alarcon et al. [26] conducted three studies using the five-factor model of trust. They found trust propensity was an important predictor of trust action, beliefs and intentions throughout the trust process. The attributes of trustworthiness are similar to the dimensions of trusting beliefs [71]. Taking these issues into account, the proposed study examines the influence of trust propensity on the consumers' trusting beliefs in an ongoing relationship with RSs.

2.3. Perceived Usefulness

In the context of IT use, perceived usefulness is defined as the extent to which a person considers that using a specific system can improve the achievement of its tasks [72]. In this research, the perceived usefulness refers to the degree to which a person thinks an RSs is useful in online shopping activity. Several previous studies have used perceived usefulness instrumental belief and found it directly linked with behavioural intention [73–76]. The technology acceptance model posits that individuals' behavioural intentions towards an information system are directly and indirectly impacted by perceived usefulness [77,78]. Earlier studies indicate that the "usefulness of an online RSs" is a critical factor in the intention of consumers to adopt and reuse RSs [15,17,32,79]. Kowatsch and Maass [79] indicate that the perception of the usefulness of online RSs impacts the intention of individuals to use the RSs and their intention to buy after using them.

2.4. Behavioural Intention

E-vendors must have the ability to engage and retain customers for long-term survival or, more importantly, to become successful. Offering recommendations for products or services to customers might be one approach to keep them engaged and assist them in their purchase decisions [80]. RSs are an important supporting tool in modern e-commerce technologies that assist customers in their decision-making process [15], while e-vendors get a competitive edge by increasing the likelihood of customers' loyalty, satisfaction and intention to purchase [32,52,54]. Even more importantly, the rise of e-commerce and online marketing is making it easier for businesses to implement modern technologies like recommender systems. In view of the opportunities, it is important to examine the characteristics that improve the possibility of a customer to reuse RSs.

The likelihood of whether a person will perform or execute a particular behaviour is defined as behavioural intention [56]. The research reported in this paper measured the behavioural intention to reuse recommender systems and focused on exploring the factors that influence doing so. In this study, behavioural intention indicates the consumers' intention to continue using recommender systems whenever they need to buy a product in the future.

2.5. Product Type as a Moderator

Alteration in product type changes RSs usage behaviour and decision outcomes [15,23,81]. Product type moderates the impact of RSs use on consumer beliefs [5,81]. Different types of information are required in evaluating different products [82].

This research examined the moderating effect of product type on the relationship between consumers' intentions to reuse RSs and their trusting beliefs, as well as their perceived usefulness. Nelson [83] theory on "search" and "experience" goods has been widely accepted in decision-making literature and has been linked extensively to recommendations in previous studies [23,30,84,85], and has been used in this research. According to the theory, a product whose quality can be measured based on its objective characteristics can be considered a search product. On the other side of the spectrum is a well-known product, which refers to a product whose quality is not calculated based on technical criteria but which relies more on subjective interpretation, subject to personal taste [83]. Table 2 shows examples of different product types that were considered in prior literature. Most previous studies have used limited varieties of products that may not embody all kinds of products and e-vendors in general. As suggested by Wang and Benbasat [25], to further validate the existing literature and to get a broader picture of the effect of product type, this study used a greater variety of products (see Table 2) and used up to date statistical measures to assess the moderation effect.

Table 2. Examples of search and experience goods.

Product Type	Examples
Search Goods [23,81,86]	Eyeglass, Cell phone, Laptop, Home Electronics, Digital Camera, Kitchen Utensils, Motorcycle Parts, Photographic Equipment, Printer, DVD Player, Network Equipment, and Electronic Accessories
Experience Goods [23,81,86]	Movies/Music CDs, Books/Magazine, Cleaning Products, Clothing, Leather Purse, Shoes, Perfume, Cosmetics, Software, Watch, Pet Supplies and recreational services.

3. Research Model and Hypotheses

The research model proposed in this paper to explain the consumers' intention to reuse RSs is presented in Figure 1.

Pu et al. [32] proposed a balanced measuring approach for assessing recommendation systems, which they termed ResQue (recommender system's quality of user experience). They investigated both users' attitudes towards the recommendation systems and the influences of users' attitudes on users' behavioural intentions in the proposed framework. Their research did not account for trust propensity, trusting beliefs, or reuse behaviour. Despite the fact that their model includes the trust construct, they only employed a small number of questionnaire items to measure trust, making it impossible to capture the various dimensions of trusting beliefs. It is also challenging to address more specific research questions solely using the ResQue Model. The main objective of this is to explore the influence of consumers' trusting beliefs on their behavioural intention to reuse RSs. The rationale of the interrelation between the underlying construct in the proposed model is derived from strong theoretical foundation of ResQue model and trust literature, as stated below.

The rationale of the relation between the trusting beliefs and behavioural intentions is based on the fundamental of the ResQue Model [32] of user centric evaluation that argues that user attitudes is positively linked with behavioural intentions. Prior research has also indicated the impact of trusting beliefs on behavioural intentions [15,17,22]. Benlian et al. [15] revealed that consumers using RSs expressed significantly higher perceived usefulness. Consumers' perceived usefulness and initial trust significantly affected their intentions to adopt RSs [17]. Increase in trusting beliefs increase adoption intentions [22].

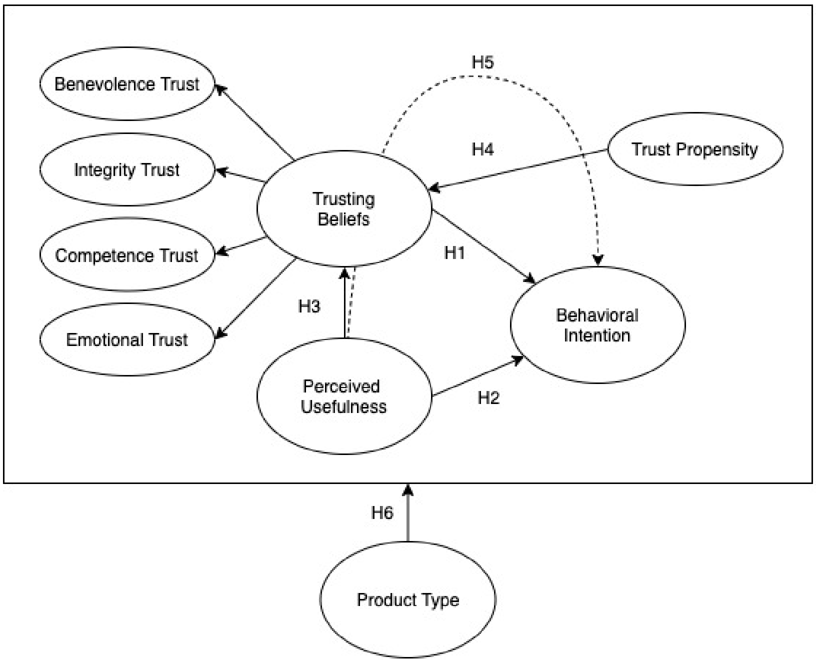

Figure 1. Overview of the research model and hypotheses.

The underlying argument of the relation between trusting beliefs and trust propensity is guided by studies that have identified trust propensity as an important antecedent of trusting beliefs throughout the trust process [26,29].

In various technology contexts, perceived usefulness was found as a cognitive belief that is salient to technology acceptance [72] and reuse [15]. Contrary to the Trust-TAM studies in the field of RSs that argues that trust stimulates usefulness [15,17], the current study argues that the increase in perceived usefulness of RSs can positively influence trusting beliefs. The relationship can be explained based on the ResQue model that asserts user beliefs (i.e., perceived usefulness) affects user attitudes (i.e., trust and confidence) [32]. A recent decision-making study in the field of IS has also linked perceived usefulness with trust and inferred that perceived usefulness influenced trust [87]. No study has linked perceived usefulness with trusting beliefs in the context of RSs. The underlying argument of the indirect effect of perceived usefulness on behavioural intention through trusting beliefs can be based on the relationship between the constructs as classified in the ResQue model (user beliefs) → (user attitudes) → (behavioural intentions) [32].

In line with the literature review and the findings discussed above, the following six hypotheses were developed to outline how consumers' trust propensity, trusting beliefs, perceived usefulness, and product type could directly and/or indirectly relate to the behavioural intentions to reuse RSs.

Hypothesis 1. *Consumers' trusting beliefs will directly affect the behavioural intentions to reuse RSs.*

Hypothesis 2. *Perceived usefulness of RSs will directly affect the consumers' behavioural intentions to reuse RSs.*

Hypothesis 3. *Perceived usefulness of RSs will have a direct effect on consumers' trusting beliefs.*

Hypothesis 4. *Consumers' trust propensity will have a direct effect on their trusting beliefs.*

Hypothesis 5. *Consumers' trusting beliefs mediate the direct effect of perceived usefulness of RSs on intentions to reuse RSs.*

Hypothesis 6. *The strength of the relationship between the constructs is significantly different in search and experience products.*

4. Methodology

A cross-sectional survey of Amazon consumers was undertaken to test the research model presented in Figure 1. The research was approved by the University of Southern Queensland's ethics committee (approval number H20REA201). Instead of a laboratory experiment with a fictitious online store and an ad hoc recommender system [88], the methods involved using a real website and an e-vendor. This was consistent with previous studies [82,89–91]. Amazon is a leading e-vendor that stocks a wide variety of products and implements personalisation, such as a recommender system that suits the need of this research [90].

4.1. Survey Instruments and Measurements

All items were assessed on a 5-point Likert scale with endpoints: '1 for strongly disagree' and '5 for strongly agree'. The survey instruments for all the constructs were adopted from valid scales with minor verbal adjustments in accordance with the study context [92] (See Appendix A).

The trust propensity construct comprises four items adapted from [17]. Measures for the trusting beliefs construct consist of thirteen items and was adopted from Ashraf et al. [23]. The perceived usefulness construct was adopted from the study of Wang and Benbasat [17]. The behavioural intentions construct comprises three items based on Benlian et al. [15]. In keeping with the advice of Kamis et al. [93], binary values were constructed for product type; it was coded as 0 for the search products (N = 171) and 1 for the experience products (N = 195).

4.2. Data Collection and Descriptive Statistics

Selected Amazon amazon.com.au (accessed on 14 December 2020) clients from Australia were sent an online survey using the Zoho Survey Platform survey.zoho.com.au (accessed on 19 February 2021). The study adopted a non-probability sampling method as it is a commonly used technique in IS research [94]. Zoho was contracted to perform the online survey, and 1361 responses were obtained. An explanation of recommender systems was provided. Respondents were briefed that Amazon typically offers recommendations under the labels "Frequently bought together" or "Compare to similar items" or "Customers who bought... also bought". The respondents were then subject to two screening questions to determine whether the respondents were current active users of Amazon and whether they had purchased at least one of the products listed in Table 2 from amazon.com.au using RSs over the last six months of responding to the survey. Using the purchased product responses, this study followed the pretested classification of product type by Ashraf et al. [23] and categorised the respondents into search product and experience product groups. This approach was consistent with previous studies based on online shopping [95,96]. Based on the survey questionnaire's screening criteria, 452 responses were considered usable and valid. An additional 86 responses were discarded for a number of reasons: acquiescence response bias was detected, where respondents answered questions without any significant variation [97]; either a univariant outlier or multivariant outlier was evident [98]. Accordingly, only 366 of the responses were used for subsequent analysis.

Table 3 indicates the study's demographic profile showing that 49.7% were males, 27.9, 28.4, 27% of respondents were 20–25 years, 26–35 years, 36–45 years, respectively. The majority of respondents were married (52.2%), held a bachelor's degree (33.6%) and were from NSW (33.3%) and VIC (31.1%). On average, respondents had used the internet for over six years, had been purchasing online for 4–5 years and had been using RSs for more than a year (mean = 3.23, SD = 1.748).

Table 3. Descriptive statistics.

Variable	Frequency	%	Mean	SD
Gender				
Male	182	49.7		
Female	184	50.3		
Age Group				
Less than 20 years	16	4.4		
20–25 years	102	27.9		
26–35 years	104	28.4		
36–45 years	99	27		
Over 45 years	45	12.3		
Marital Status				
Single	156	42.6		
Married	191	52.2		
Widowed	1	0.3		
Divorced	10	2.7		
Other	8	2.2		
Education				
Certificate	86	23.5		
Diploma	39	10.7		
Bachelor Degree	123	33.6		
Master Degree	92	25.1		
Doctorate/PhD	24	6.6		
Other	2	0.5		
Geographic Location				
VIC	114	31.1		
NSW	122	33.3		
QLD	65	17.8		
WA	32	8.7		
SA	15	4.1		
TAS	7	1.9		
ACT	10	2.7		
NT	1	0.3		
Internet usage, online purchasing experience and RSs usage experience				
Internet usage experience *			7.42	1.406
Online purchasing experience **			4.85	1.477
RSs usage experience ***			3.23	1.748

* Anchored at 1 = "Less than 1 year" and 8 = "more than 7 years" ** Anchored at 1 = "Less than 1 year" and 6 = "more than 5 years" *** Anchored at 1 = "Less than 6 months" and 7 = "more than 5 years".

5. Results

Partial least squares structural equation modelling (PLS-SEM) inspection of the research model was executed with SmartPLS (v3.3.3) software [99]. Evaluating PLS-SEM findings entails two stages: analysis of the measurement model in stage one and analysis of the structural model in stage two [100]. To assess the possible moderating effect of the product type, PLS-MGA was performed as it is considered the most efficient way of determining moderation across multiple relationships [101].

5.1. Analysis of Measurement Model

The scales' reliability, convergent validity and discriminant validity were tested as part of the measurement model evaluation based on the recommendation of [101] and [102]. As reflected on the outcomes of the evaluations (see Table 4), all the item loadings met the cut-off value of 0.70 [102], all the constructs' Cronbach's alpha (α), composite reliability (CR), Dijkstra–Henseler's rho (ρ_A) and the average variance extracted (AVE), were above the accepted thresholds of 0.70 [103], 0.70 [102], 0.70 [101] and 0.50 [104], respectively. Internal consistency was achieved.

Table 4. Factor Loadings, reliability and validity.

	Item Loadings	α	ρ_A	CR	AVE
Trust Propensity		0.877	0.881	0.915	0.730
TP1	0.880				
TP2	0.857				
TP3	0.865				
TP4	0.815				
Trusting Beliefs		0.952	0.953	0.958	0.637
BT1	0.756				
BT2	0.785				
BT3	0.720				
CT1	0.785				
CT2	0.820				
CT3	0.801				
ET1	0.833				
ET2	0.822				
ET3	0.828				
IT1	0.814				
IT2	0.772				
IT3	0.811				
IT4	0.820				
Perceived Usefulness		0.923	0.923	0.936	0.618
PU1	0.764				
PU2	0.782				
PU3	0.782				
PU4	0.801				
PU5	0.787				
PU6	0.745				
PU7	0.804				
PU8	0.815				
PU9	0.792				
Behavioural Intentions		0.878	0.878	0.925	0.804
BI1	0.886				
BI2	0.897				
BI3	0.907				

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TP: Trust Propensity. Trusting Beliefs includes: BT: Benevolence Trust, CT: Competence Trust, IT = Integrity Trust, and ET = Emotional Trust.

Heterotrait Monotrait (HTMT) Ratio procedure was assessed to determine the discriminant validity of the constructs. The threshold value of the HTMT ratio was 0.90 [105]. As depicted in Table 5, all the values of HTMT in this study are less than the threshold value of 0.90. This study ran a bootstrap routine to assess the confidence interval for HTMT, and the upper confidence interval limit was below 1 [106] (see Table 6). Discriminant validity was attained.

Table 5. Discriminant Validity using HTMT.

	BI	PU	TB	TP
BI				
PU	0.885			
TB	0.804	0.846		
TP	0.639	0.652	0.743	

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs, TP: Trust Propensity.

Table 6. HTMT inference.

	Original Sample (O)	Sample Mean (M)	2.50%	97.50%
PU -> BI	0.885	0.887	0.836	0.930
TB -> BI	0.804	0.804	0.720	0.874
TB -> PU	0.846	0.846	0.789	0.894
TP -> BI	0.639	0.638	0.560	0.713
TP -> PU	0.652	0.650	0.573	0.724
TP -> TB	0.743	0.743	0.672	0.803

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs, TP: Trust Propensity.

5.2. Analysis of Structural Model

An examination of collinearity is essential prior to the structural model analysis to ensure it does not bias the regression result [101]. In this study, there were no collinearity issues, as the multi-collinearity test result revealed that all the VIF values ranged from 1.531 to 2.715 and were below the recommended threshold of 3.3 [107].

The structural model's explanatory capabilities were evaluated using an R^2 value to reflect the explained variance of the dependent constructs [102]. The R^2 values were 0.701 for trusting beliefs and 0.664 for behaviour intentions, which explained more than 70.1% and 66.4% of the construct, respectively. All of these R^2 values that were reported signified a substantial model [108]. Using the blindfolding procedure, the Stone–Geisser's Q^2 value for the complete model was obtained to determine the model's predictive relevance. The value of 0.529 for BI revealed the large predictive accuracy of the PLS path model [102]. A bootstrapping routine of 5000 subsamples [101] was used to explore the significance of the path coefficients. Figure 2 shows the result of the structural model inspection for better illustration.

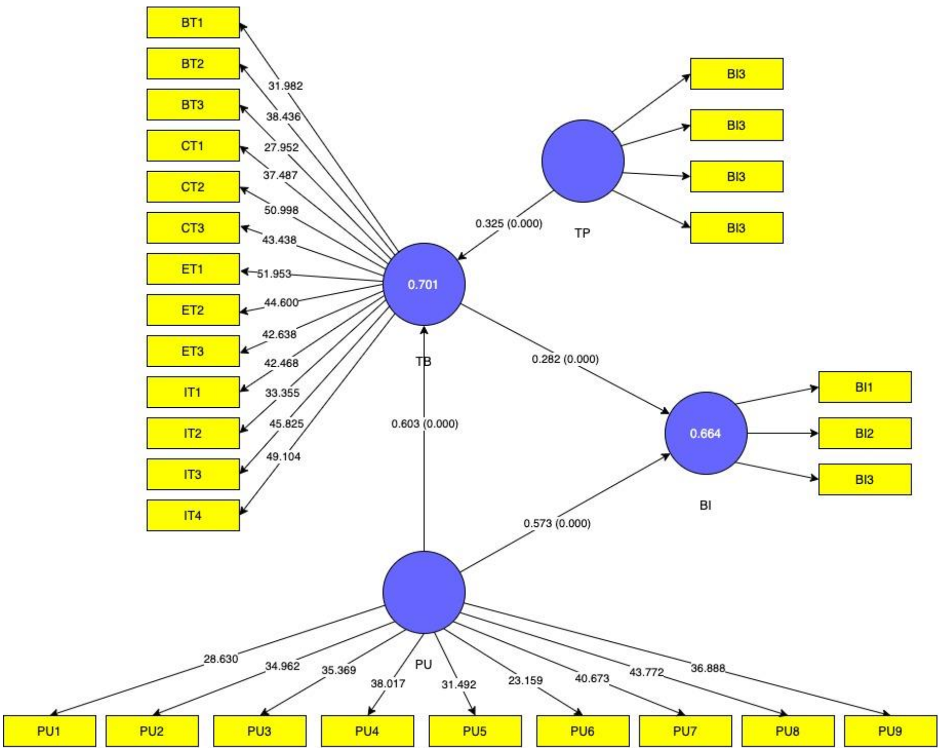

Figure 2. Result of structural model inspection (Complete sample). Note: BI: Behavioural Intentions, PU: Perceived usefulness, TB: Trusting Beliefs, TP: Trust Propensity. (0.000) indicates all direct paths are (Sig. at $p < 0.001$).

As exhibited in Table 7, all four direct effect hypotheses were supported. Trust propensity was observed to have a positive impact on trusting beliefs (β = 0.325, t = 8.035,

$p < 0.001$). Perceived usefulness was positively linked to trusting beliefs (β = 0.603, t = 16.196, $p < 0.001$). Behavioural intentions to reuse RSs was found to be positively affected by perceived usefulness (β = 0.573, t = 7.644, $p < 0.001$) and trusting beliefs (β = 0.282, t = 3.483, $p < 0.001$).

Table 7. Results for direct relationships (Complete sample).

	Path Coefficient	Standard Deviation	T Statistics	*p* Values
TB -> BI	0.282	0.081	3.483	0.000
PU -> BI	0.573	0.075	7.644	0.000
PU -> TB	0.603	0.037	16.196	0.000
TP -> TB	0.325	0.040	8.035	0.000

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs, TP: Trust Propensity.

5.3. Mediation Analysis

The results indicated that the total effect of perceived usefulness on behavioural intentions was found to be significant and positive (β = 0.743, t = 25.522, $p < 0.001$). When the mediator was integrated into the model, the effect was reduced, but the direct relationship remained significant (β = 0.573, t = 7.644, $p < 0.001$). Furthermore, the inclusion of the mediator (trusting beliefs) in the analysis was also found to be significant (β = 0.170, t = 3.329, $p < 0.05$). The result reveals a partial mediation. Consequently, H5 was accepted (see Table 8).

Table 8. Mediation analysis (Complete sample).

	Total Effects		Direct Effects			Indirect Effects		
	β	t-Value	β	t-Value		β	t-Value	*p*-Value
PU -> BI	0.743	23.522	0.573	7.644	PU -> TB -> BI	0.170	3.329	0.001

Note: PU: Perceived usefulness, BI: Behavioural Intentions, TB: Trusting Beliefs.

5.4. Multi-Group Analysis

An essential and logical step prior to conducting PLS-MGA is to estimate the invariance of composite models [109]. This step is important to evaluate whether the composition has different meanings in each group, as it can otherwise mislead the structural coefficients' group-specific results. MICOM was assessed to establish the measurement invariance [109].

The steps involved in the MICOM process were: assessment of configural invariance (Step 1), assessment of compositional invariance (Step 2), and finally, determination of the equality of composite mean values (Step 3a) and variances (Step 3b) [109]. To perform a multi-group analysis, at least partial measurement invariance needs to be established [109].

First, the assessment of configural invariance was executed. In SmartPLS 3, running MICOM automatically accomplishes configural invariance [101]. Second, compositional invariance was assessed, focusing on the creation of identical composite scores throughout the groups. SmartPLS was used to perform a permutation analysis with 5000 resamples [103]. As illustrated in Table 9, the correlation of the composite scores between the indicator weights obtained from the search products and experience products groups were equal to 1 or greater than 5%-quantile. It can be concluded that both groups are compositionally invariant. The third step was to assess the equality of composite mean values and variances. Equality of composite mean and variances can be confirmed, and full measurement invariance is attained if the confidence intervals of the differences of mean values and variances between the two groups contain zero [109]. To validate this step, permutation results were analysed to determine the mean values and variances between the construct scores of the search products and experience products groups that differ from each other. As illustrated in Table 9, the equality of means and variances was successfully verified; hence full measurement invariance was attained.

Table 9. Results of 3-step measurement invariance testing using permutation.

	Step 1	Step 2			Step 3(a)			Step 3(b)			
Constructs	**Configural Invariance**	**C = 1**	**5% Quantile of C_u**	**Compositional Invariance**	**Differences**	**Confidence Interval (CIs)—Mean Value**	**Equal Mean Value**	**Differences**	**Confidence Interval (CIs)—Variances Value**	**Equal Mean Value**	**Measurement Invariance**
BI	Yes	1.000	1.000	Yes	0.228	[−0.210; 0.204]	Yes	-0.113	[−0.305; 0.308]	Yes	Full
PU	Yes	1.000	1.000	Yes	0.189	[−0.209; 0.203]	Yes	0.123	[−0.321; 0.324]	Yes	Full
TB	Yes	1.000	1.000	Yes	0.253	[−0.216; 0.204]	Yes	0.107	[−0.253; 0.252]	Yes	Full
TP	Yes	0.999	0.999	Yes	0.405	[−0.213; 0.199]	Yes	0.073	[−0.245; 0.251]	Yes	Full

Note: TB: Trusting Beliefs, PU: Perceived usefulness, BI: Behavioural Intentions, TP: Trust Propensity.

After full measurement invariance was attained, PLS-MGA was performed to detect the differences between search products and experience products using the Welch-Satterthwait test [101]. Table 10 illustrates the differences between the path coefficients of the two groups. None of the paths between the two data sets (Search products and experience products) was found to be significantly different; H6 was not supported.

Table 10. Multi-group analysis (PLS-MGA) using Welch-Satterthwait test.

Relationship	Search Product Path (N = 171)	Experience Product Path (N = 195)	Path Coefficients Difference	t-Value	*p*-Value
TB -> BI	0.339	0.248	0.091	0.547	0.585
PU -> BI	0.528	0.597	−0.069	0.441	0.660
PU -> TB	0.665	0.571	0.095	1.293	0.198
TP -> TB	0.261	0.356	−0.095	1.151	0.251

Note: TB: Trusting Beliefs, PU: Perceived usefulness, BI: Behavioural Intentions, TP: Trust Propensity.

The research further uses PLSpredict (see [110]) to generate holdout sample-based point predictions in PLS path models to see whether integrating emotional trust improves prediction accuracy over using the model without emotional trust. Table 11 shows that integrating emotional trust into the model improves prediction compared to the one that does not include it. This is evident in the results; the inclusion of emotional trust improves the Q^2_predict values of a model's constructs over a model without it [111]. To summarise, while the model without the inclusion of emotional trust remains impactful, the model with the inclusion of emotional trust is more efficient in explaining consumers' behavioural intentions to reuse RSs.

Table 11. PLSpredict assessment.

With Emotional Trust				Without Emotional Trust			
Constructs	**RMSE**	**MAE**	**Q^2_predict**	**Constructs**	**RMSE**	**MAE**	**Q^2_predict**
BI	0.606	0.439	0.643	BI	0.604	0.438	0.640
TB	0.558	0.389	0.694	TB	0.566	0.398	0.684

Note: BI: Behavioural Intentions, TB: Trusting Beliefs.

6. Post Hoc Analyses

In the research reported on in this paper, the aim was to examine the influence of trusting beliefs on behavioural intentions to reuse recommender systems, emphasising the effect of trust propensity, perceived usefulness and product type. To accomplish the present study's objective, a cross-sectional questionnaire survey was undertaken using an integrated model (Figure 1), which included six accompanying hypotheses.

As predicted by the hypotheses associated with the direct effect of trusting beliefs and perceived usefulness (i.e., H1 and H2), the results revealed that trusting beliefs and perceived usefulness was significant and positive indicators of the behavioural intentions to reuse RSs. These results substantiate prior findings in the literature [15,17].

In accordance with the prediction of H3, it was found that perceived usefulness has a significant and positive effect on the consumers' trusting beliefs. The PLS-SEM result has indicated that the effect of perceived usefulness is more significant than trusting beliefs in predicting consumers' intentions to reuse a recommender system. The most remarkable result that emerged from the data is the direct relation of trust propensity on trusting beliefs, confirming our hypothesis H4. The result widens our knowledge on the effect of trust propensity in later evaluations.

As predicted by H5, trusting beliefs significantly and positively mediate the direct effect of consumers' perceived usefulness of RSs on behavioural intention to reuse RSs. This result supports the existing body of literature [15,17].

Surprisingly, contradicting H6, the relationship between the constructs is statistically insignificant in search and experience products and deserves a much-extended comprehensive discussion in future studies. This finding contradicts earlier results reported in the literature [15,23,112]. Consumers perceived lower trusting beliefs in the context of experience products as compared to search products [23]. Perceived usefulness was more significantly affected in the search product than the experience product [15]. Choi et al. [112] identified differences in the effects of social presence on RSs reuse intentions concerning product type. The nature of the shopping environment online can provide a possible explanation for the result of the current study. Hedonic excitement occurs mainly when the consumer uses a product [113]. This can be particularly the case in the context of the online environment in which search and experience products are quite unlikely to be experienced before the purchase; a consumer may not feel any noticeable differences [11,113–115]. Building on this view, the online shopping environment can explain why the product type has no moderating effect on consumers' intentions to reuse recommender systems. A number of experts have provided further support for our argument [11,115].

7. Contributions

7.1. Theoretical Contributions

The current study aimed to address the ignorance of important factors such as emotional trust and trust propensity in the past trust-centred studies based on RSs by empirically testing a model that estimates the effect of a comprehensive framework of trusting beliefs on customers' reuse of RSs. In the current study, an important antecedent of trust, i.e., trust propensity, indicated a significant and direct relationship with trusting beliefs. The current research bridges the literature gap, illustrating how an antecedent of trusting beliefs, i.e., consumers' trust propensity is related to trusting beliefs of the recommender system in an ongoing relationship. The empirical results of the study indicated that the proposed model has good explanatory as well as good predictive power. It indicates that the integration of subjective factors such as trust propensity and trusting beliefs provides a theoretical basis for explaining the customers' behavioural intentions to reuse recommender systems. The significant strength of the mediating effects was also shown to be an intriguing finding; the results revealed that trusting beliefs was an important mediator of reuse intentions. The research model which integrated perceived usefulness as an antecedent of trusting beliefs, is a distinctive contribution of this study. Another contribution of this study also included a typical combination novelty that includes concepts from IS literature (recommender systems, perceived usefulness), trust literature (trust propensity, trusting beliefs) and the use of up-to-date as well as the most efficient statistical approach (PLS-MGA) to test the moderation effect of product type. This study also used the PLSpredict technique that focuses on the predictive model assessment, most notably a model's predictive validity or out-of-sample predictive power [110]. It is evident that the model with the inclusion of emotional trust is more efficient in explaining consumers' behavioural intentions to reuse RSs. An emotional trust can extend a relationship much beyond a typical business or transactional relationship as it is built on a strong foundation of social-emotional relationships [116]. A strong favourable feeling towards a trustworthy object, i.e., emotional trust, may motivate trust in addition to good rational reasoning that builds cognitive trust [117].

Both the theory and the extant literature guided the inclusion of the product type as a moderator. Surprisingly, the result of PLS-MGA showed an insignificant difference between the effect of search products and experience products regarding consumers' behavioural intentions to reuse the recommender system. Although the outcome did not find support for the hypotheses of product type as moderator, this result may contribute to our understandings of Australian consumers' intentions to reuse the recommender system. More significantly, perhaps, this study can also be used by researchers and academicians to improve the understanding of customers' intentions to reuse RSs.

In terms of methodology, this paper is among the first to apply MICOM and PLS-MGA to investigate the moderation effect of product type on the consumers' behavioural intentions to reuse the recommender systems. This study also uses the PLSpredict technique to determine the appropriate causal-predictive model.

7.2. Practical Contributions

The present study has implications to practice as well. The findings of the research suggest that e-vendors should design recommender systems that are not only useful and convenient, but also trustworthy. Trustworthiness in RSs can be strengthened by providing the reason for proposing a certain recommendation or recommendation set in the form of textual explanations [47,118,119]. An example of textual explanation used by Amazon is the "Frequently Bought Together" section. Higher degrees of trusting beliefs in recommender systems can also trigger a higher degree of consumer intentions to reuse recommender systems. The finding of this research also suggests improving emotional trust formation as it contributes to behavioural intention to reuse recommender systems. Emotional trust can be fostered more effectively by incorporating RSs that provide immediate feedback (e.g., those incorporate elements of the phone conversation) and available channels for interpreting communication cues (such as sound, video, text, and so on) [120,121]. E-vendors may exploit useful techniques such as providing textual explanations for the recommended items, explanations indicating a high average rating of a recommendation or using natural language to provide an explanation based on the content features to improve customer trust in recommendation systems [118,122,123]. E-vendors may also equip recommender systems with explanatory components to more closely imitate the flow of information between humans to encourage a customer to feel trusted and reduce customers' utilisation concerns [123]. Trust is highlighted as a key antecedent in the online environment for other behaviours including loyalty [124] and purchase intentions [125]. There exit significant possibilities for this to influence other customers' behaviour if such design aspects of the RSs can affect trusting beliefs and trusting intentions. Trust propensity is an important determinant of consumer trusting beliefs on the recommender system in an ongoing relationship. Even if some customer groups may be targeted, it is clearly beyond the control of an e-vendor to manipulate a consumer's trust propensity.

E-vendors before expecting purchase behaviour must understand the need of establishing consumer trust, because this makes e-commerce marketing efforts long-term and more relational instead of transactional. This changes potential key performance indicators (KPIs) from being solely a sales-based approach to an engagement-based approach.

8. Limitations and Future Research

Notwithstanding the contributions of the research, it is not without limitations. First, the data have been collected from users of Amazon of Australia; the model should be replicated in other contexts for results triangulation and better generalizability. Second, this research was restricted to Amazon's recommender systems that use collaborative filtering method. Third, the omission of actual behaviour is another impediment, as some scholars disagree with intentions as a proxy for reuse behaviour. Some academics postulate that the causal association between intentions and behaviour is unpredictable [126]. Fourth, a major source of contamination is in the reliance on self-reports to assess trust propensity resulting in common method variance. While it may affect the strength of the relationships, certain studies suggest that the problem is not as typical as assumed [127].

Further research should explore the proposed model using a less famous e-commerce platform that uses recommender systems with a different underlying method of algorithms such as content-based filtering or hybrid filtering. Future research should determine actual reuse and consider a comparison of male and female online shoppers in a cross-group study. Prospective research may also examine other possible factors such as perceived risk, different recommender systems, discounted products, and attitudes towards the e-vendor's recommender systems. Future research should assess the impact of dimensions of trusting beliefs differently on consumers' intentions to reuse RSs. Further, even though the current study showed no moderating effect of product type on consumers' behavioural intentions to reuse RSs, future studies might examine other variables and contexts that could have a strong moderating effect on behavioural intentions in the product type.

9. Conclusions

The present study used a trust centred lens to address an important gap in the IS literature. The present study estimated the role of trust propensity on the influence of consumers' trusting beliefs of RSs in a continuing relationship, a novel aspect not previously considered in RSs research. The influence of consumers' trusting beliefs and perceived usefulness of RSs on behavioural intentions to use RSs in a continuing relationship was also assessed. Building consumers' trusting beliefs is a crucial element for e-commerce companies to succeed. This research used PLSpredict technique to generate holdout sample-based point predictions in PLS path models to see whether integrating emotional trust improves prediction accuracy over using the model without emotional trust. The results were significant without emotional trust but the inclusion of emotional trust to the model was more efficient in explaining consumers' behavioural intentions to reuse RSs. It implies that trusting beliefs should be considered as a comprehensive framework that comprises cognitive (integrity, benevolence and competence) and emotional trust. The study also explored the moderating effect of product type. Contrary to our expectation this study finds that the consumers do not perceive search products or experience products differently. The somewhat contradictory result could be attributed to the assumption that customers could not perceive any difference between search products and experience products due to the influence of the nature of the online shopping environment. This research is a small but significant step towards understanding the effects of subjective factors such as consumers' trust propensity and trusting beliefs and their effect on intentions to use recommender systems in an ongoing relationship. Finally, several recommender systems are now available on mobile apps [128]. It is hoped that the present study would prompt new questions and further research that will lead to guidance for e-vendors seeking to increase their customers' trust and ultimately sales. Future research should extend our research to the context of the mobile application.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. The Measures

Perceived Usefulness (PU) (Wang & Benbasat, 2005)	
PU1	Using RS enabled me to find suitable <product> more quickly.
PU2	Using RS improved the quality of analysis and searching I performed to find suitable <product>.
PU3	Using RS made the search task for <product> easier to complete.

PU4	Using RS enhanced my effectiveness in finding suitable <product>.
PU5	Using RS gave me more control over the <product> search task.
PU6	Using RS allowed me to accomplish more analysis than would otherwise have been possible.
PU7	Using RS greatly enhanced the quality of my judgments.
PU8	Using RS conveniently supported all the various types of analysis needed to find suitable <product>.
PU9	Overall, I found RS useful in finding suitable <product>.
Trust Propensity (TP) (Wang & Benbasat, 2007)	
TP1	It is easy for me to trust a person/thing.
TP2	My tendency to trust a person/thing is high.
TP3	I tend to trust a person/thing, even though I have little knowledge of it.
TP4	Trusting someone or something is not difficult.
Trusting Beliefs (TB) (Ashraf et.al., 2019)	
BT1	The RS was competent in recommending the required product.
BT2	The RS was an expert to recommend the product according to my preference.
BT3	The RS was effective in recommending the required product.
CT1	I believe that the RS dealing with me was in my best interest.
CT2	I believe that the RS dealings with me felt like it would do its best to help me.
CT3	I believe that the RS dealings with me to find the best product.
IT1	I believe the RS was truthful.
IT2	I believe the RS was unbiased.
IT3	I believe the RS was honest.
IT4	I believe the RS was sincere and genuine.
ET1	While relying on the RS for my buying decision, I felt assured.
ET2	While relying on the RS for my buying decision, I felt comfortable.
ET3	While relying on the RS for my buying decision, I felt contend.
Behavioural Intention (BI) (Benlian et. al., 2012)	
	If you needed to purchase a similar product in the future, how likely is it that …
BI1	… you would intend to continue using RS in the future?
BI2	… you would predict your use of this RS to continue in the future?
BI3	… you plan to continue using this RS in the future?

Appendix B. Instructions Provided to Participants

This study stated that Recommender systems (RSs) are web-based technology that recommends tailored products or services to customers based on their past buying behaviour or their specified preferences or the preference of other like-minded customers.

Please note: Amazon typically uses recommender systems to offer recommendations under the labels "Frequently bought together" or "Compare to similar items" or "Customers who bought … also bought".

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