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Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce

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ABSTRACT

E-commerce is becoming a major contributor to the worldwide economic system, owing to its adaptability and ease of use for both customers and service providers. Recommender systems are embedded in most modern e-commerce websites, as efficient tools for guiding users to view additional items provided by e-commerce portals. These items are matched with customers' interests depending on their current activities, or on preferences stated in their profiles. As service providers are more concerned with the long-term behavior of customers, and specifically customer loyalty (which bears directly on the long-term success of e-commerce websites), most recommender systems have been developed to consider that aspect. This study investigates the major factors in the loyalty formation of female online shoppers through an e-commerce recommender agent. A new model is introduced, developed, and analyzed for helping to improve e-commerce customer loyalty via the recommender systems. Based on the implications of the results, we can understand research constructs and highlight research outcomes to help in managing recommender systems more effectively.

1. Introduction

The onset of internet services and "Web 2.0″ technologies has provided the commerce community with hundreds of brands from e-stores worldwide for users, and a context in which the users can browse items, compare prices, and take advantage of great offers [1]. In recent years, the growth of online sales profits has exceeded that of most traditional market sales, as customers seek to find new markets outside their domestic areas [2]. As a result, new trading models have been introduced into the global economy [3]. Previously-unworkable business schemes are being developed, and are emerging with the advent of online systems [4]. E-commerce systems make it possible for people to make transactions through wireless networks or through the internet medium, eliminating the need to physically visit a marketplace. The massive advancement of e-commerce systems has created an interest in theoretical and practical research to investigate the keys to the advancement and profitability of such systems.

However, the massive growth in e-commerce sales has been accompanied with user frustration, owing to the vast amount of information that users must progress through to make a purchase. Several competitive e-commerce websites seek to attract users, which can lead to an information overload problem. An information overload problem occurs when a user faces an excess of information that exceeds his/her limited capacity to process information. Consequentially, the information overload problem will require additional intellectual effort from the user to make decisions regarding items he/she viewed. As it is, the user must spend a significant amount of time evaluating products and their prices before proceeding to a purchase process.

As a vital part of modern e-commerce websites, recommender systems serve as supporting tool in the decision-making process, by providing suitable recommendations to users [5]. Many studies have indicated that the integration of recommender systems into e-stores enhances the quality of choices and users' overall confidence regarding their choices, with reduced levels of search complexity [6–9]. Recommender systems work efficiently to guide users to view more items in catalogues that match their interests, depending on their current activities or on their preference profiles. Recommender systems provide benefits to both service providers and customers [8]. For users, a

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recommender system can improve the search efficiency in finding desirable products, whereas service providers gain an advantage from increasing the users' likelihood of satisfaction, intention to purchase, and loyalty [8,10,11]. It is essential to inspect the aspects that can trigger consumers to accept consultations presented to them by recommender systems, and to measure the compatibility of the generated recommendations with the desired outcomes of recommender systems.

Previous research studies have addressed how to improve recommender systems by means of the design of the operation mechanisms and the accuracy of the generated algorithm [12–14] Although accuracy metrics can enhance users' perceptions of the quality of the generated suggestions, the accuracy of the algorithm can only partially reflect the overall user experience [15]. There remains a need to inspect the potential factors affecting peoples' willingness to use/accept recommender systems, through subjective measures. Several theories, based on physiological and sociological backgrounds, have been advanced to provide potential justifications for the user acceptance and adoption of a specific technology [16]. A clear relationship has been established between customers' attitudes and their behavioral intentions to purchase products or to benefit from online services in e-markets [17–19]. Customer intentions indicate actual user behavior, and have been highlighted as being the best determinant of customer behavior. A purchase intention reflects a consumer's actual plan to purchase a targeted item or acquire a desired service. The purchase intention also provides an indication of the user's adoption of online systems [20]. In that regard, an understanding of actual user behavior can be achieved by inspecting the factors that can improve the user's intention [21]. In the real world, companies are more interested in users' long-term behavior, as reflected by repetitive purchases and increased profits for e-market websites. Some empirical research studies have investigated the effects of using a recommendation agent on users' behavioral intentions in a short-term scenario [10,22]. However, service providers are more attentive to the deep-rooted enhancement of the experience of their commercial hosts, which can be measured by trust and satisfaction (as prerequisites of a loyalty formation process).

E-commerce customers can easily switch among various websites to view more products and choices, which can negatively affect e-vendors, as the difficulty of maintaining loyal customers increases dramatically [23–27] One crucial issue of concern for e-vendors is understanding the formation of a sense of loyalty by e-commerce customers [28–32]. Online loyalty, repurchase intentions, continuous intentions, or e-loyalty (for short) can be considered as reflecting customers' behavioral intentions to buy from an e-vendor, without changing to other e-vendors [28,33]. Accordingly, it is essential to explore the aspects that might increase a user's likelihood to frame a persistent relationship with the e-shop via the recommender system. Hence, it is important to measure user loyalty towards an online recommendation website. Loyalty has traditionally been investigated by extensively focusing on objective behavioral dimensions, through the examination of statistics that measure customers' repurchase behavior. Recently, researchers have argued that there is a need to concentrate on the attitude dimension of customer loyalty, which can be evaluated through a user-centric evaluation in the context of recommendation system research. The attitude dimension of loyalty involves studying what goes on in the customer's mind [34].

In view of the above, identifying the cognitive factors that derive satisfaction, trust, and loyalty in an e-commerce recommender system scenario (through the supported literature) would provide an important contribution to the theory in this context. Therefore, the motivations behind this imperial investigation lie within three main objectives. The first objective draws on an insight to fill the hole in ongoing research, by examining and inspecting the benchmarks for the success of recommendation agents, focusing on a user-oriented point of view. The second objective is to propose an integrative research model that combines different aspects to contribute to the development of an abiding quality relationship with the system. The third objective is to validate the proposed model, which will help uncover how the various aspects relate to customer loyalty. This, in turn, can assist vendors in effectively controlling and improving the long-term relationship between customers and recommender systems, by involving those factors in the e-commerce recommendation agents. The results of the analysis are presented in the conclusion section, as well as the theoretical and practical implications for both researchers and e-service vendors. As far as we know, few research studies have focused on the correlation between the numerous quality aspects of the recommendation engine and their outcomes, and the longstanding interplay between the user and the agent [11].

This study is structured into seven main parts. Section 2 presents a literature review of previous studies in the same context. Section 3 investigates the background of this study, focusing on previously adopted theories in the same context. Section 4 presents the development of the model and hypotheses. The survey design and pilot study are clarified in Section 5. The empirical outcomes are discussed in detail in Section 6. Finally, the conclusion is introduced in Section 7.

2. Literature review

The availability of various competitive e-commerce platforms has encouraged researchers to concentrate on loyalty as a measure of system success. Online loyalty, or e-loyalty for short, has been deeply investigated in the literature, with the proposition of several definitions of "loyalty" with various concentrations of attitudinal or behavioral loyalty perspectives. However, an objective measure of loyalty, e.g., as the purchase ratio, is not sufficient to reflect a user's true sense of loyalty [27,35]. Recently, researchers have argued that there is a need to focus on both the behavioral and attitudinal dimensions of customer loyalty [36]. Definitions of loyalty in previous studies focused on aspects of attitude [30,35,37–39], intention [26,28,29,40,41], or behavior [13,14,21,24].

As a recommender system is an influential tool in modern online market technologies, it is crucial to inspect the factors that might increase a user's likelihood of building a profitable long-term relationship with a recommender system. A few studies have investigated how to improve customer loyalty in regard to recommendation agents by adopting user-oriented perspectives. Of particular relevance to our research, Yoon et al. [11] assessed the influence of two moderator variables: customers' product knowledge regarding a specific domain, and users' experiences in customer loyalty from using recommendation agents. The proposed framework was developed based on a cognition–affect–behavior model. The study tested the framework empirically, using between-subject experiments in a lab-controlled environment. The results indicated the negative impact of customer product knowledge on customer loyalty towards the website that hosts the recommender engine. The results also revealed that the relationship between satisfaction and customer loyalty is not affected by the moderating role of the customer's online experience. Although we based our model on the same theoretical model of cognition-affect-behavior, our model integrates factors of (1) website quality and (2) recommendation agent quality in a more detailed manner, in an attempt to analyze and determine the specific factors that have significant impacts on customer loyalty towards the recommendation agent. Our model also considers trust as in important antecedent factor that promotes user loyalty towards the recommendation agent.

Trust is a significant factor that helps users to overcome the perceived risks related to the adoption of e-commerce systems, and influences customer behavior [119]. The element of trust has a compelling direct impact on the use of a certain technology [42]. Trust is considered as a base for building and retaining a longstanding relationship with a system [21,43]. The positive tie between trust and loyalty has been affirmed in previous literature [28]. The phenomenon of trust has been thoroughly researched in studies related to the acceptance of e-commerce systems, and in recommender system studies that adopt system-centric and user-centric evaluation approaches [8,10,44]. Users must trust the accuracy of the recommendations provided by the system

[45]. In the context of recommendation engines, it is more likely that users who trust the recommender system will buy the products from the online market site [46]. Consumers must feel that the recommender system will produce convenient recommendations that will help them to reach better decisions and find better products matching their interests. Many and different elements can contribute to stable trust building towards recommendation engines [47]. During the research on the literature, we noticed that earlier research studies had concentrated on interpreting individual drivers of trust establishment in recommender systems [8,10]. Nilashi et al. [10] explored the factors that promote user trust towards the recommender system in two commercial websites: Amazon and Lazada. This work defers to their work focusing on long-term behavior, which can be investigated through an extensive model of loyalty formation factors. In our research, we aim to investigate users' trust in the recommender system as a mediating factor that can improve customer loyalty towards the recommender system.

Pu et al. [8] presented a balanced measurement framework for evaluating a recommendation system, which they referred to as ResQue (recommender system's quality of user experience). In the proposed framework, they assessed both the users' attitudes towards the recommendation agent, and the influences of users' attitudes towards users' behavioral intentions. Their work resembles the work of Nilashi et al. [10]; which focused on behavioral intentions towards a system by measuring users' purchase intentions. However, their work did not consider the quality of the website hosting the recommender system as an indicator of user attitudes and behavioral intentions.

Knijnenburg et al. [15] presented a study that adopted an evaluation framework for recommendation systems. The framework went beyond analyzing the accuracy of the generated algorithm, to a deep inspection of objective and subjective measures regarding the quality of recommender systems, based on a user-oriented evaluation. The comprehensive work presented in their study links objective system aspects to objective user behavior through perceptual subjective system aspects. Thus, the study adopted an abstract approach, in which they focused on general concepts within users' experiences, without focusing on lower-level concepts. The objective aspects of the system entailed recommendation agent features that could affect users' experiences with the system, such as the underlying algorithm, interface and interaction design, and presentation of the generated recommendations. Users' perceptions of the objective quality criteria were captured through subjective measures. The authors conducted two controlled experiments and four field trials to assess the validity of the proposed framework. The study indicated the importance of subjective system aspects and experience variables in characterizing and understanding users' experiences with recommendation agents. Their framework builds a robust platform for the evaluation of user experiences with recommendation agents. However, the definition of lower-level constructs, along with the use of a robust tool for measuring these constructs, must be employed to answer more specific research questions. We will address these in our research.

3. Theoretical background

Loyalty (or repurchase intention) has been investigated, measured, and conceptualized, by using different theoretical models to examine users' behavioral and attitudinal experiences with a system under study. Drawing from Oliver's [48] research, long-term adoption of a system can be represented by four stages of loyalty formation, and can be measured implicitly or explicitly. Whereas explicit loyalty relates to users' actual overt behaviors, implicit loyalty is developed through users' internal decision-making processes [43]. However, researchers have argued that relying on behavioral measures from consumers' previous purchase patterns is insufficient [27]. Hence, researchers have begun to concentrate on attitudinal aspects of loyalty to express users' long-term intentions.

Most previous studies have conceptualized loyalty in utilitarian contexts [49,50] by using traditional models of users' adoption, such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) [51]. Although many theories are available and used to explain the adoption of information technologies in information system research, the existing theories, as summarized in Venkatesh et al. [52]; are mainly directed towards a cognitive orientation. The TAM model highlights that the intention to adopt an information technology (IT) is influenced by the perceived usefulness and perceived ease of-use of the IT [53], whereas the UTAUT theory posits that the intention to accept and use an IT is affected by four main constructs: performance expectancy, social influence, effort expectancy, and facilitating conditions [52]. In traditional IT adoption studies, the users are mostly employees of an organization, who use traditional IT to achieve specific tasks related to their jobs [51]. The adoption of an IT in these contexts is dominated by cognitive factors [51]. However, as the recommender system works as a personalized advice-giving embedded tool within a hosting website, it requires a comprehensive effort to understand users' acceptance and adaptation intentions in a long-term scenario. The recommendation agent's adoption might encompass both cognitive and affective decisions, as recommendation agents' users are often considered as general IT users or customers. Generally, e-commerce customers choose products that they cannot experience before the actual purchase process, which reduces the domination of cognitive perspectives in the context of uncertainties regarding the product or the seller. Thus, this study focuses on the long-term adoption of recommender systems, with the advent of both rational and emotional perspectives. In that regard, the user experience with a recommender system entails both cognitive and affective dimensions. This study follows and extends this line of research by delineating the cognitive and emotional perspectives, and by investigating their respective roles in the long-term adoption of a recommendation agent.

In this research, the recommender engine is considered as a decision support tool for aiding a user in his/her decision, and as an information system that the customer uses to achieve a specific task. Hence, we are focusing on the impacts of the recommender system on user decisions, as represented by the attitudinal behavior and user perception towards different quality factors related to the recommendation agent. Several theories have been adopted to justify the proposed hypotheses, and will be elaborated on in detail in the following subsections.

To understand the current position of loyalty research in an online market context, we conducted a survey of previous studies in the electronic commerce loyalty context, as presented in Table A1 (see the Appendix). As seen from the table, several theories have been used as theoretical backgrounds to explain loyalty formation in e-commerce and m-commerce studies. The cognition-affective-behavior model was adopted in six studies [11,26,30,54,55]. Looking at the direct antecedents of loyalty in the investigated studies, we notice that satisfaction is regarded as a direct driver of loyalty formation in 30 studies, whereas trust is considered as a direct factor for promoting consumer loyalty in 18 studies.

3.1. Cognition-affect-behavioral model

We drew the theoretical research background from attitude theories by Eagly and Chaiken [56] and Bagozzi [57] and Lazarus [58]. Eagly and Chaiken [56] presented the attitude formation theory, in which user attitudes are formed mainly based on three dimensions: cognitive, affective, and behavioral. Bagozzi [57] reformulated the attitude-behavior relationship by using the intermediation of emotional reactions between cognitive appraisals and coping responses. Lazarus [58] indicated the impacts of appraisals of internal and situational conditions on emotional responses, which in turn influence coping activities.

By adopting the cognition-affect-behavior model, we organized the proposed research model based on three phases. First, the information that users obtain regarding the attitude object forms the cognitive factors, and formulates users' beliefs. Hence, when a user interacts with the

Table 1
Cognition, affective and behavior in previous literature.

Reference	Context	Cognitive	Affect	Behavior
Yoon et al. [11]	Recommender system	• Recommendations' quality	• Satisfaction	• Loyalty
Lam et al. [55]	B2B	• Customer value	• Satisfaction	• Loyalty
Taylor et al. [60]	Pop-up restaurants	• Perceptions of experiential value	• Relationship quality (Trust/Satisfaction)	• Positive WOM • Return intention • WTP
Chiou [54]	Internet Service Providers	• Attributive service satisfaction	• Overall satisfaction	• Loyalty
Safa & Solms [26]	E-commerce	• Benevolence • Enjoyment • Clear Shopping process • Convenience benefits • Security • Reliable Payment Systep	• Trust • Satisfaction	• Loyalty
Lin & Wang [30]	M-commerce	• Perceived value • Trust	• Satisfaction	• Satisfaction
Chen & Phou [61]	Tourism	• Destination Personality • Destination Image	• Trust • Satisfaction • Attachment	• Loyalty
Kwon & Vogt [59]	Tourism	• Belief in place marketing	• Satisfaction	• Involvement in Decision Makin • Personal Influence
Thaichon & Quach [62]	E-commerce	• Service Quality	• Commitment • Trust • Value • Satisfaction	• Loyalty

system, cognitive factors are formed to create beliefs. Second, the experience with the system generates emotional preferences for framing the affective component. The model implies the intermediation of emotional factors between users' beliefs and behaviors. The emotional factors can be represented by positive or negative judgments regarding the attitude object, to thereby frame the affective reaction [59]. Third, behavioral factors are connected to individuals' behaviors in relation to the attitude object.

In the hypothesized model, the quality of an online market will cause a sense or perception that can prompt positive emotions in users, which are represented by customer satisfaction. Customer satisfaction is an affective variable. The quality attributes of the online recommendation engine can trigger an affective trust towards the system. The website quality, recommendation quality, and transparency are regarded as cognitive variables. The behavioral intention to continue a relationship with the system, as represented by loyalty, is provoked by users' feelings of trust and satisfaction. In our research, customer loyalty is a behavioral variable, and is represented by a repurchase intention. Customer loyalty is a tendency to act positively towards a service provider. By applying this framework to e-commerce recommendation sites, we can determine the intermediating effects of the hedonic dimensions of satisfaction and trust on customer loyalty. Thus, the conceptual framework provides a basis for hypothesizing that the customer satisfaction intermediates the effects of the quality of the website hosting the recommender engine on customer loyalty, and customer trust mediates the effects of the recommendations' quality and transparency on customer loyalty. Table 1 presents some cognition, affective, and behavior dimensions from previous literature.

3.2. Theory of human information processing

This theory describes humans' limited capacity to process information. In this regard, the huge development of e-commerce has provided users with a wide variety of choices and a massive volume of information. This can give users more alternatives to analyze, to thereby gain more insights regarding the right products to buy. Although the advance of e-commerce has benefits (both actual and anticipated), the massive amount of information can cause the information overload problem, and challenge human cognitive abilities. New techniques are required to analyze these amounts of information, such as recommender systems and information filtering systems [11]. Recommender agents can help users overcome the information overload problem in two ways: first, by helping users in their decision-making process, specifically when the decision must be made within a short time; and second, by helping users to evaluate the overwhelming number of different choices. The recommendations provided to users can increase users' capacities in processing data for decision-making, and can aid users in their purchase decisions. Hence, it would be compelling to analyze the impacts of recommendation engines on users' repurchase behaviors.

3.3. Theory of interpersonal similarity

In the interpersonal similarity theory, a similarity between different parties infers a perception of social closeness between the parties [11, 63]. Accordingly, the degree of attraction between two parties depends on the degree of similarities between the parties, in different aspects such as behavior, attitude, background, and personality [64]. In the previous literature, attraction is developed based on higher levels of similarity between individuals, and the interpersonal similarity affects the processing of information regarding other individuals, by providing a sense of closeness between similar users [65]. As highlighted by Mcknight et al. [66]; individuals apply a type of cognitive classification process, in the form of unit grouping, to develop trust. Hence, in collaborative filtering recommender systems, the set of recommended items is generated based on the similarities between users in tastes and preferences [7]. Applying a collaborative filtering approach to generate recommendations that match users' interests to other users with similar tastes can increase trust. The interpersonal similarity theory implies that quality recommendations lead to customer trust of the recommendation engine.

3.4. Theories of trust formation

An effective recommender system must gain the confidence of its customers regarding the products they recommend, and regarding the recommendation approach used to generate the recommendations [64]. Hence, the trust phenomenon is considered as a major issue in several studies in the e−commerce context generally [67], and in the recommendation agent context specifically [10,64]. Trust formation theories were scrutinized deeply in previous research, and this research highlighted several dimensions of trust [64]. Customers and recommender systems build a long-lasting relationship of trust over time [68]. Trust is formulated when the user uses the system and acquires knowledge regarding the system over time [66]. Knowledge-based trust is formed

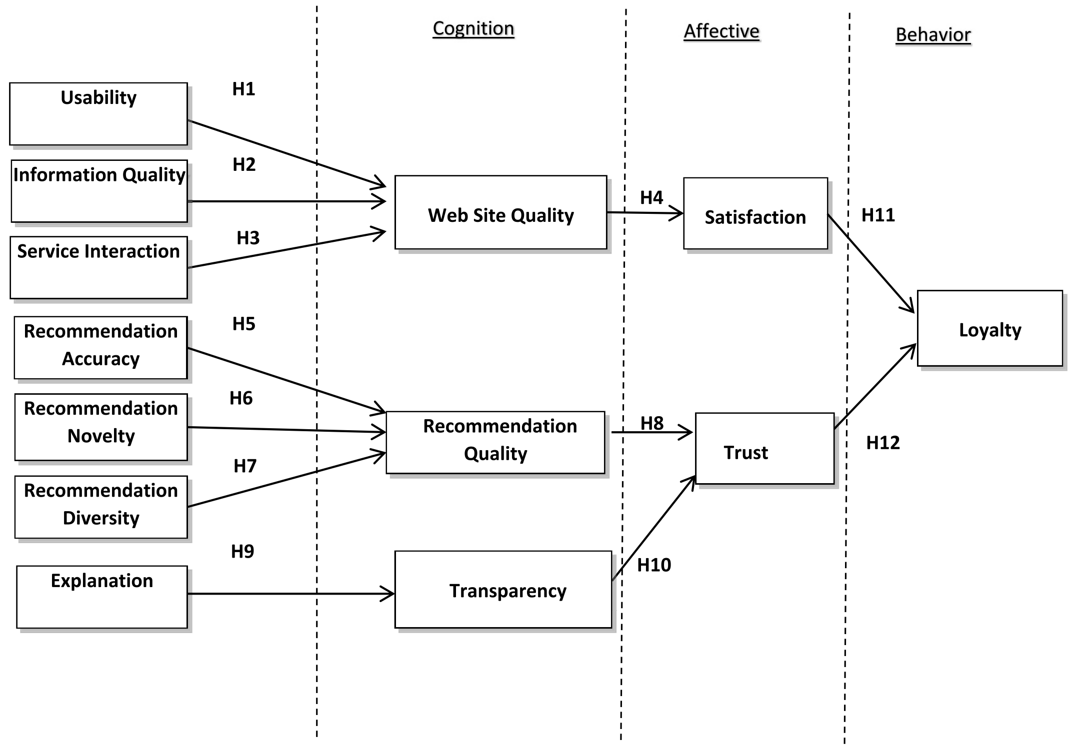

Fig. 1. Loyalty model for E-commerce recommender systems.

when the user can predict and anticipate the outcomes of the recommendation engine [64], and can be represented by the generation of accurate recommendations that match user expectations. However, the usefulness of the recommendation agent implies the presentation of novel recommendations, which can also trigger negative feelings. The solution to such a contradiction is to embed the novel and surprising item within a list of accurate recommendations [69]. Moreover, the agency relationship between the customer and the recommendation engine indicates assigning the task of item evaluation and elicitation to the recommender system, whereas the user is assigned to the principal's role. The interactive relationship between the recommender system and the customer is based on the product evaluation and screening process, which is performed by the recommender system to generate suitable suggestions for the user. In addition, the provision of an explanation by the recommender engine to justify how these recommendations match user preferences will enhance user trust with the system [70]. Wang and Benbasat [71] inspected the effects of the existence of an explanation tool on building trust early with users. After investigating the influence of three types of explanations (why, how, and trade-off), the results revealed different impacts on each of the trusting beliefs being studied.

Finally, the trust of recommendations is seen as an antecedent to behavioral intentions [8]. Pu and Chen [68] linked trust with customers' positive intentions to purchase, transact, and repurchase from the hosting online store. Hence, the relationship between trust and loyalty, which we adopted in the conceptual model, can be inferred from the strong theoretical background in the literature.

Table 2
Demographic results of the participants.

	Item	Frequency	Percent
Gender	Female	300	100%
Age	<20	60	20
	20–30	240	80
Experience with Amazon in the last six months.	Once	82	27.3
	1-3 Times	95	31.7
	More than 3 times	123	41

3.5. WebQual model

As an entrenched tool in most online markets, recommendation engines communicate with users through the recommender hosting website [10,72]. Hence, the quality attributes of the hosting site will influence users' overall satisfaction, which will consequentially increase the probability of customers' repurchase behaviors. Website quality attributes have been discussed widely in the literature, in terms of the quality of the information provided to users, the interaction process with users, and the usability of the website [73,74]). These attributes have been linked in the previous literature to higher levels of user satisfaction [73–76]. Website interface quality has been demonstrated as a prerequisite for e-vendor success. The development of a physiological effects chain has been investigated extensively in the literature, from perceived quality to loyalty [33,77,78]. Consequentially, a three-phase chain, starting from quality attributes with the mediation of satisfaction to a permanent commitment towards the system, has been presented, reviewed, and evaluated in many previous studies. It has been proven theoretically that a perception of high quality leads to long-lasting loyalty, which in turn drives longstanding financial benefits. Hence, investments in website quality were linked to increasing customer loyalty, driving the long-term corporate profitability. However, little research has been conducted to examine the effects of website quality attributes on satisfaction, and in turn on users' continuous intentions in the context of recommendation engines. Thus, considering website quality as a benchmark for a service supplier [79] and developing an appropriate research model that integrates quality factors in a research context will help in understanding users' perceptions of the quality factors of the recommendation host site, and the impacts of these factors on satisfaction and loyalty.

The WebQual model was developed in 2000 as WebQual 1.0. It was the first instrument of WebQual, which was deployed for measuring the quality of a business school website. A refinement of WebQual 1.0 containing 24 questions was released after the analysis of pilot study results. The final version of WebQual 1.0 reflected aspects for measuring subjective qualities, i.e., experience, information, communication and integration, ease of use, experience, and information. However, one drawback of WebQual 1.0 is its limitations in measuring the interaction dimensions of each quality, especially in an e-commerce context [80]. Continuing this line of research, WebQual 1.0 was enhanced and refined by analyzing and reviewing previous works on service quality. WebQual 2.0 was developed after a comparison with "SERVQUAL", which led to adopting significant questions and deleting redundant questions to thereby generate a 24-question instrument. However, although WebQual 2.0 is considered a strong instrument for measuring the quality of a service interaction, the quality of the information has lost the richness that had been presented in WebQual 1.0. To resolve this drawback, WebQual 3.0 was developed and tested in the online auctions field, and contained three aspects for measuring website quality: service interaction quality, information quality, and site quality. Still, to focus on users' perceptions of website quality rather than designers' aspects, WebQual 4.0 was developed, and contains usability as a replacement for site quality [80].

Choosing a suitable method for measuring website quality has been studied by researchers in the fields of marketing and information systems. The WebQual model [80] measures user perceptions of online merchant quality numerically, using a powerful questionnaire tool [10]. WebQual was developed using an iterative approach to data collection and analysis [80]. As our research is an attempt to capture quality aspects from the "voice of the customer" using subjective measures, it is appropriate to use the WebQual model in this study. Moreover, as our research is based on user-oriented evaluations, we adopted WebQual 4.0, as it contains the usability dimension.

4. Research model and hypotheses

The objective of this research concerns analyzing the concepts of website quality, recommendation quality, recommender system transparency, satisfaction, trust, and consumer loyalty in online recommender merchant settings. Thus, different hypotheses have been proposed, as derived from the strong theoretical background and literature. The interrelationships between the underlying constructs have been integrated in the conceptual model for further testing. The mediating effect of consumer satisfaction on website quality and loyalty and the mediating role of trust on the impact of recommendation quality in regard to consumer loyalty have both been carefully examined. The research model is presented in Fig. 1.

4.1. Website quality and customer satisfaction: hypotheses (1–4)

The website quality attributes investigated in this research are derived from the WebQual 4.0 model, in which usability, service interaction quality, and information quality constitute the overall website quality. In that regard, the online website hosting the recommendation engine is the only interaction panel that connects customers to the system [72]. Following this stream of research, an e-commerce customer's level of satisfaction will depend on the attributes of the hosting website. Our assumption in this research relies on these website attributes to judge website quality. Website quality attributes have a direct and positive influence on user satisfaction [75]. As the recommender system is typically a component of the website, we can conclude that such online quality attributes might also indicate to what extent consumers are satisfied with the embedded recommender engine.

The WebQual 4.0 model considers that the dimensions of WebQual 4.0 will affect the online site quality. Hence, depending on this assumption as confirmed in the literature, we present the first three research hypotheses regarding website quality. These three hypotheses have been previously adopted by various authors [10,81]. Website quality aspects have an impact on consumers satisfaction, which was established in the early literature [74–76]. Based on this, Hypothesis 4 is offered, i.e., that the quality of the website hosting the recommender system has a positive effect on user satisfaction with the recommendation agent. To summarize:

- Hypothesis 1 (*Usability→Website Quality*). The usability of the website hosting the recommender system will positively affect the perceived website quality.
- Hypothesis 2 (*Information Quality→Website Quality*). The quality of the information in the website hosting the recommender system will positively affect the perceived website quality.
- Hypothesis 3 (*Service Interaction→Website Quality*). The quality of the service interaction of the website hosting the recommender system will positively affect the perceived website quality.
- Hypothesis 4 (*Website quality →Satisfaction*).The perceived quality of the website hosting the recommender system will positively affect consumer satisfaction.

4.2. Recommendation quality and trust: hypotheses (5–8)

A key prerequisite of a user's positive experience with the recommendation engine is the quality of the generated recommendations. Previous research on recommendation engines concentrated on measuring recommendation quality, using the accuracy of rating predictions [82]. Although the mean absolute error can assess the degree to which the predicted ratings match the actual ratings, error measures alone cannot evaluate the extent to which the generated recommendations are valuable to users and match their needs and requirements. Therefore, it is important to test the perceived quality attributes empirically, by applying user-oriented studies that move beyond the accuracy of predictions, and focus on measuring users' experiences with the recommendation engines [11]. Following the previous literature in determining the possible factors that constitute the overall perceived quality of recommendations, several factors have been identified as quality factors for recommendation agents, such as novelty, diversity, and serendipity [8]. Accuracy, novelty, and diversity can affect user perceptions of the quality of the recommender system. Some authors

Table 3
Constructs reliability and validity after deleting the indicators with lower outer loadings for the main study.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
ACU	0.855	0.912	0.775
DIV	0.729	0.847	0.648
EXP	0.727	0.844	0.644
LO	0.874	0.922	0.799
NOV	0.783	0.874	0.698
RQ	0.848	0.887	0.568
SATIS	0.884	0.912	0.635
SERV	0.907	0.927	0.647
TRANS	0.768	0.865	0.681
TRUST	0.93	0.947	0.782
USAB	0.909	0.927	0.613
WEBQ	0.834	0.9	0.751

have argued that not all of these factors have a positive effect on customers' perceptions of recommender system quality. Knijnenburg et al. [15] hypothesized that the perceived accuracy of a recommender system influences the user experience. Novel items involve items that trigger user interest, educate the user, and enable him/her to discover new items [8]. There is a conflict between novel and serendipitous items. However, Herlocker et al. [7] argued that novelty is a different concept than serendipity, as novelty is only limited to newly generated items. In contrast, serendipitous items move beyond new items, to cover surprising items. However, in user-oriented studies, the fuzzy difference between these two concepts can mislead the user. Hence, we adopted novelty as a quality factor in our proposed model. Jannach et al. [83] implied that user perceptions of recommendation quality can be negatively affected by novel recommendations. Nilashi et al. [10] argued that the impact of these factors on the perceived quality of the recommender system depends on the domain and on the purpose of the recommender system. They suggested that in the e-commerce context, novelty has a strong positive effect on the perceived quality of recommendations (in contrast to the context of, e.g., movies). The recommender system quality refers to the capability of the recommender system to provide recommendations that match users' interests. The recommender system quality is often considered as an essential factor for the formation of trust in a recommender system [10]. The quality of recommendation engines depends on several factors such as diversity, novelty, and accuracy, which will consequentially affect the online users' trust and continuous intentions to adopt the recommendations [10]. Hence, the proposed hypotheses are listed as follows:

- Hypothesis 5 (*Recommendations' Accuracy →Recomendations' Quality*)

The accuracy of the generated recommendations will positively affect the perceived quality of the recommendation agent.

- Hypothesis 6 (*Recommendations' Novelty →Recommendations' Quality*)

The novelty of the generated recommendations will positively affect perceived quality of the recommendation agent.

- Hypothesis 7 (*Recommendations' Diversity →Recommendations' Quality*)

Diversity in the generated recommendations will positively affect perceived quality of the recommendation agents.

- Hypothesis 8 (*Recommendations' Quality →Trust in Recommender System*)

The perceived quality of the generated recommendations will positively affect consumer trust in the recommendation agent.

4.4. Satisfaction, trust, and loyalty: hypotheses (12, 13)

User satisfaction is often considered as a pass-key for the continuing online market achievements, and as an antecedent to loyalty formation [28,88,89]. User satisfaction is an important factor for measuring the quality of information system implementation [74]. It was recognized in the early literature that satisfaction is important to relationship continuity [26].

In e-commerce, the seller task is delegated to online merchants, and the user relies on the merchant to proceed to the purchase decision. Hence, the recommendation engine extends the seller figure in an artificial manner, by suggesting items to consumers and persuading them to purchase online [90]. Furthermore, recommendation engines are employed as trust objects that can guarantee good consumer services to users, to thereby gain their endorsement and commitment [10,64]. This implies that high-quality recommendations will promote user trust. Furthermore, the positive relationship of trust to loyalty has been confirmed in the literature [28]. Users who trust the recommender system are more likely to buy products from e-commerce websites, and to adopt recommendation agents in the long-term [46]. Hence, the next hypotheses are listed as follows:

- Hypothesis 12 (*Satisfaction →Loyalty*)

Satisfaction has a positive effect on loyalty towards the recommendation agent.

- Hypothesis 13 (*Trust →Loyalty*)

Trust has a positive effect on loyalty towards the recommendation agent.

5. Survey design and pilot study

4.3. Explanation, transparency, and trust: hypotheses (9–11)

In regards to evaluating recommender systems from user perspectives, the transparency of the system is very important, as it allows users to feel more confident in the system and accept it [84]. In addition to the quality of the recommendations, transparency has a direct and positive impact on trust-building towards the recommendation agent [10,22,85,86]. Transparency refers to the capability of recommender systems to convey information to the customer, by providing explanations to the customer regarding why items were recommended. Explanations are of great importance to recommender systems, and increase the transparency of the recommender system by showing how recommendations are suggested to customers [87]. Several studies have explored the influence of the presentation of explanations as a mechanism for trust promotion [68,70]. Users dislike blind recommendations, and they search for justifications regarding the recommended items [84]. The next hypotheses are summarized as follows:

- Hypothesis 9 (*Exlanation →Recommender System Transprrancy*)

Explanation facilities in the recommendation agent will positively affect the perceived transparency of the recommendation process.

- Hypothesis 10 (*Recommender System Transperancy →Trust in the Recommender System*)

Transparency in the recommendation agent will positively affect consumer trust in the recommendations made by the agent.

5.1. Survey design

Based on a deep review of the literature, the questionnaire survey was refined to gather the information needed to prepare for the quantitative research. The quantitative research comprises analyzing the developed hypotheses, and empirically validating the final model for adoption. The design and deployment of the questionnaire are very important steps, and involve deep research to ensure that the research methodology is acceptable. The questionnaire of this study is written in the English language. The respondents in this study are Arabic-native speakers. As college students who study their courses in the English language, the majority of the respondents have the basic English abilities required to understand and answer the questionnaire.

During the design of the questionnaire, two important aspects must be considered. First, the research objectives must be reflected carefully, and second, the characteristics of the audience must be well-identified [91]. To achieve an insightful conclusion, the questions of the survey must carefully follow the research objectives. Furthermore, the target audience must be considered during the questionnaire writing process, to aid the researcher in developing a questionnaire with understandable items [91]. The main objective of the questionnaire survey is to identify the constructs that have an important role in loyalty formation for e-commerce websites, through recommender systems. The relationships among the research constructs were tested according to the proposed model, to validate them in parallel with the main objective of the study. To study the effectiveness of the research constructs in the context of loyalty formation for online recommendation sites, the survey was designed based on the literature.

In this regard, the statements of the questionnaire were chosen from original references used and applied in various research papers [10,11]. Choosing previously applied statements will increase the questionnaires' validity and reliability. The designed questions might follow a structured form, or a close-ended form with ordered choices to allow the respondents to easily choose answers from among a set of choices. The survey of this study contains five main sections. Before the respondent answers the survey, he/she must fill out some basic/background information to help the researcher investigate the differences among respondents. Ordinal response scales, i.e., "Likert Scales", are used in the survey to represent the degree or intensity of belief or feeling, such as poor, fair, neutral, good, and very good. The ranges for the Likert scale vary from: 0–4, 1–7, and 1–9 [91]. The attitudes of the respondents in our study are captured through a 5-point Likert scale by answering the survey questions. A 1–5 Likert scale is used, as follows: 1 for strongly disagree, 2 for disagree, 3 for neutral, 4 for agree, and 5 for strongly agree. The items of the questionnaire are presented in Table A2 (see the Appendix).

5.2. Pilot study

To confirm the reliability and validity of the designed instrument and research procedure, a pilot study was conducted before finalizing the designed instrument and using it in the main study. The pilot study followed the content validity to test questionnaire items with participants who represent the targeted audience, and to catch any potential problems or misunderstanding of questionnaire items in the research design or in the execution of the deployed instrument. This was conducted by analyzing and evaluating the results before completing the full study, which might be costly and time-consuming. A pilot study can also work as a training survey, in which beginner evaluators can practice collecting and analyzing data to avoid any unforeseen mistakes in the final study. A pilot study can also be used to check that the research protocol, research design, and questionnaire items are aligned with the main goal of the study, and can help in answering research questions.

The data collection was conducted within Imam Abdulrahman Bin Faisal University. At the beginning of the study, a pilot study among 64 participants was conducted in the university within two weeks. The main task for the users was to go to Amazon.com, inspect and choose an outfit of four pieces, and put it in the shopping cart. Hence, by asking respondents to choose four pieces, respondents were given a chance to interact with the system, and to check the generated recommendations.

The survey enabled participants to add comments regarding the clarity of survey questions. Some of the participants indicated a perceived similarity among some of survey questions in the same construct. Hence, the survey questions were reviewed, and some of the questions were replaced. Following the data collection process, the SmartPLS software package was used to analyze the measurement model in the study. Based on the results of the analysis and on the comments received from respondents, minor changes were made to the questionnaire items to make them clearer to participants in the main study.

6. Empirical results

6.1. Data collection

Determining the appropriate population of interest before data collection is a very important step for the development and success of the research. Based on the context of our study, i.e., e-commerce generally and recommendation engines specifically, a search was conducted for similar studies based on user-aligned evaluations. Notably, college students were used as a research sample in several studies [10,65,92]. Students were used as a sample in studies in the e-commerce context generally [28,93–96], and in the specific context of e-commerce recommender systems [10,97,98]; Zhang et al., 2011; [92]. As a large portion of internet users in general and those participating in e-commerce activities specifically (and represented by the term "Net Generation" [92]), college students were chosen as the sample population in our research. College students are commonly used for large scale internet surveys. as they are computer and internet users [99]. According to Wen et al. Wen et al. [96]; students are considered as a vast group of web users. This allows college students to perfectly resemble a population of e-commerce customers [99]. Students can also represent online consumers, as online consumers are more educated and younger than traditional consumers. Further reasons for choosing students include their understanding of e-services, their familiarity with electronic media, and their usage of e-services for communication and commercial transactions [100]. In view of the above, college students are representative of the population. The study was conducted with the participation of 300 female students from Imam Abdulrahman Bin Faisal University. The participants of the study were students from computer and business departments. Most of the students were between 20 and 30 years old, and had used the website more than three times in the last six months before the data collection. Table 2 illustrates the demographic information of the respondents.

6.2. Data analysis

The relationships between constructs were analyzed using partial least squares and structural equation modeling (SEM) [117]. Using SEM to assess the relationships among the independent variables and dependent variables in research models has been recognized in the research community for quantitative research. SEM incorporates the benefits of factor analysis, path analysis and multiple regression analysis, and establishes a robust methodology to evaluate the relations between constructs. All of the above encouraged us to use SmartPLS (www.SmartPLS.com) for analyzing the results of the survey. The outcomes of the different tests of the inner and outer models will be reported in detail below.

6.2.1. Assessment of the measurement model

To evaluate the quality of the outcomes of the analysis phase, several evaluation criteria must be addressed in different applicable tests in the research measurement model. Assessing the measurement model implies a distinction between the evaluation approaches for reflective and formative constructs, which must be applied and reported in detail. The assessment of the reflective constructs includes three main tests, regarding the convergent validity, internal consistency, and discriminant validity. The first measurement of the quality of the convergent validity is the outer loading of each indicator, with a minimum threshold of 0.7 [101,102]. The outer loadings of the constructs' associated indicators to most of the research factors are higher than 0.708. According to Hair et al. [101]; indicators with outer loadings less than 0.4 must be removed. Following this rule, we deleted all indicators with outer loadings less than 0.4, which unsurprisingly represented two reverse-scale questions, S6 and S8. Another measure of the convergent validity is the average variance, which we extracted to test and confirm the positive correlation between indicators in the same construct, and to

Table 4
Fornell-Larcker criterion.

	ACU	DIV	EXP	LO	NOV	RQ	SATIS	SERV	TRANS	TRUST	USAB	WEBQ
ACU	0.88											
DIV	0.63	0.805										
EXP	0.359	0.336	0.803									
LO	0.533	0.415	0.429	0.894								
NOV	0.437	0.344	0.55	0.454	0.836							
RQ	0.612	0.482	0.459	0.497	0.511	0.753						
SATIS	0.601	0.459	0.411	0.653	0.429	0.483	0.797					
SERV	0.623	0.462	0.375	0.624	0.463	0.496	0.717	0.804				
TRANS	0.414	0.311	0.623	0.436	0.805	0.379	0.447	0.444	0.825			
TRUST	0.529	0.387	0.422	0.812	0.43	0.521	0.703	0.668	0.437	0.884		
USAB	0.639	0.495	0.444	0.647	0.439	0.505	0.716	0.753	0.441	0.664	0.783	
WEBQ	0.842	0.557	0.358	0.617	0.487	0.539	0.624	0.676	0.467	0.631	0.717	0.866

confirm that each construct met the minimum threshold of 0.5 [101, 103]. To check if the internal consistency test provides reliable results, we check each of the Cronbach's Alpha and composite reliability criteria; both must meet a minimum threshold of 0.7 [101]. After deleting the indicators with outer loadings less than 0.4, the results of the measurements of Cronbach's Alpha, composite reliability, and average variance met the required minimum threshold for the constructs' reliability and validity, as presented in Table 3. The final test of the reflective measurement model is the discriminant validity test, which entails two main tests with respect to cross loadings and the Fornell-Larcker criterion. Discriminant validity measures the extent to which a construct is truly distinct from other constructs. The Fornell-Larcker criterion is presented in Table 4, whereas cross loading is presented in Table A3 (see the Appendix). The result of the Fornell-Larcker criterion test indicates that the correlations between the construct and other constructs are less than the square root of the average of that construct. In the cross-loading test, the outer loadings of the indicators of each construct are higher than their cross loadings, which is confirmed in the results.

In the research model, we have only one formative contrast (information quality). For testing the formative construct, we conducted tests on collinearity statistics, and the significance of path coefficients. The acceptable value of the variance inflation factor (VIF) should be below 5 [101], which is fulfilled for each indicator in the formative construct. The results of the collinearity statistics are presented in Table 5. The path coefficients' significance is measured using a bootstrapping algorithm, as presented in Table 6. As we can see from the results, only two indicators achieved the minimum threshold t-value of 1.96 (WQI3, WQI7). Following Hair et al. [101]; we check the outer loadings of each indicator that fails to achieve the minimum threshold. All indicators have outer loading values greater than the minimum threshold (0.5) [101], so we retained the indicators for subsequent analysis.

6.2.2. *Assessment of the structural model*

The assessment of the structural model follows confirmation of the validity and reliability checks of the model constructs. The relationships between constructs are presented in the structural model, and are evaluated through four main tests: path coefficient, coefficients of determination, effect size, and Stone-Geisser's Q^2 value. In the next subsections, we report the results of different tests regarding the structural model. The final structural model is presented in Fig. 2.

6.2.2.1. Path coefficient (hypotheses testing). Following the confirmation of the validity and reliability of the measurement model, we need to validate the structural model. To test the significance and relevance of the coefficients, we applied a bootstrapping routine and examined the t-values and p-values (Hair et al., 2015). P-values are used to measure the strength of relationships between variables, whereas t-values are used to test the significance of coefficients. The hypotheses' testing results are presented in Table 7. As can be seen, most of the hypotheses are

Table 5
Collinearity statistics (VIF) for formative measures of the main study.

Construct	Measurement	VIF
Information Quality	WQI-1	1.927
	WQI-2	2.233
	WQI-3	2.765
	WQI-4	2.996
	WQI-5	3.077
	WQI-6	2.966
	WQI-7	2.161

supported, except for H2 (information quality does not have a significant effect on website quality). However, the main coefficients in the research model proved to be significant ($p < 0.01$). Website quality has a direct effect on customer satisfaction ($p < 0.01$). Satisfaction, in turn, significantly affects loyalty ($p < 0.01$). The quality and transparency of recommendations significantly affects the trust towards the recommender system ($p < 0.01$), and trust has a compelling effect on loyalty towards the recommendation engine ($p < 0.01$).

6.2.2.2. Coefficients of determination (R^2 value). The predictive power of the model is tested using coefficients of determination. This test uses the percentage of variance in an endogenous construct, which can be demonstrated using its exogenous variables (Hair et al., 2015). The R^2 values for endogenous constructs range from 0 to 1, with higher numbers indicating stronger predictive accuracy (Hair et al., 2015). The results of the coefficients of determination test are presented in Table 8. As we can see, the values of R^2 range between 0.339 and 0.673. As our research is considered a consumer-oriented research aiming to explain consumer satisfaction and loyalty, a value of 0.2 for R^2 is considered high (Hair et al., 2015).

6.2.2.3. Effect size (f^2 value). The effect size test tests one exogenous construct, in terms of the strength of its contribution to explaining a certain endogenous construct using the value of R^2. Cohen [104] suggested that if f^2 ranges between 0.02 and 0.15 the effect is small, whereas the effect is medium if it falls within the interval of 0.15–0.35. Lastly, if the f^2 value is greater than 0.35, the effect is large. Table 9 shows the effect sizes. As presented in the table, trust has a large effect on loyalty towards the recommender system. Satisfaction has a small effect on loyalty. Website quality has a large effect on satisfaction. Recommendation quality has a medium effect on trust. Transparency has a small effect on trust. Information quality has no effect on website quality. Service quality has a small effect on website quality, and usability a has medium effect on website quality. Looking at the quality factors for recommender systems, novelty has small impact on recommendation quality, whereas accuracy has a medium effect on recommendation quality. Surprisingly, diversity has a small effect on recommendation quality.

Table 6
Significance assessment of the formative construct.

Construct	Measurement	Significance			
		Outer Weight	Outer Loadings	t-value>1.96	P Values
Information Quality	WQI-1	0.182	0.739	1.531	0.126
	WQI-2	0.098	0.758	0.745	0.456
	WQI-3	0.279	0.828	2.401	0.016
	WQI-4	0.114	0.793	0.89	0.373
	WQI-5	0.127	0.8	0.992	0.321
	WQI-6	−0.091	0.741	0.725	0.468
	WQI-7	0.491	0.888	3.925	0

6.2.2.4. Stone-Geisser's Q^2 value. The final test we conducted for evaluating our structural model concerns the predictive relevance (Q^2 value). For each dependent construct, the predictive relevance of the path model can be indicated by Q^2 values larger than zero for its endogenous reflective constructs. To find the value of Q^2, we performed a blindfolding procedure. The outcomes are presented in Table 10. As shown in the table, all endogenous constructs have Q^2 values larger than zero.

6.3. Summary of model fit results

The summary of the results shows that:

i. Both trust and satisfaction have positive effects on loyalty towards the recommendation agent, with β values of 0.699 and 0.161, respectively.
ii. Recommendation quality and transparency have direct effects on trust towards the recommendation agent, with β values of 0.415 and 0.28, respectively.
iii. Website quality has a strong effect on user satisfaction, with a β value of 0.624.
iv. Both novelty and accuracy have direct effects on recommendation quality, with β values of 0.29 and 0.405, respectively.
v. Both website usability and service interaction have significant effects on website quality, with β values of 0.464 and 0.296, respectively.
vi. Diversity has a small effect on recommendation quality, with a β value of 0.127.
vii. Information quality has no effect on website quality.

7. Conclusion

7.1. Theoretical contributions

Studies in various fields have been conducted to consider the factors that can infer customer loyalty towards online merchants. As discussed previously, several theories were used to structure our loyalty formation model. Our model is based on the well-recognized cognition-affect-behavior model. The results of the study analysis on the Amazon e-commerce website are consistent with preceding studies in the literature, having shown the structural relationship between website quality and user satisfaction, and that between satisfaction and customer loyalty. Furthermore, the outcomes of the study indicated the effects of the recommendation quality on users' trust, and the effect of trust on customer loyalty towards the recommendation agent. These results were compatible with previous literature in this domain. In that regard, Yoon et al. [11] confirmed the structural relationship between customer satisfaction and loyalty in an e-commerce recommender system context, and Nilashi et al. [10] indicated the relationship between recommendation quality and customer trust towards recommendations agents.

Our research confirms the three-phase model of the quality-satisfaction-loyalty chain [48], from users' perceptions of quality before the purchase process, to customers' loyalty to rational and emotional processes. The information system continuity can be determined by users' attitudes, which are shaped by both cognitive and affective perspectives. Although previous studies using traditional

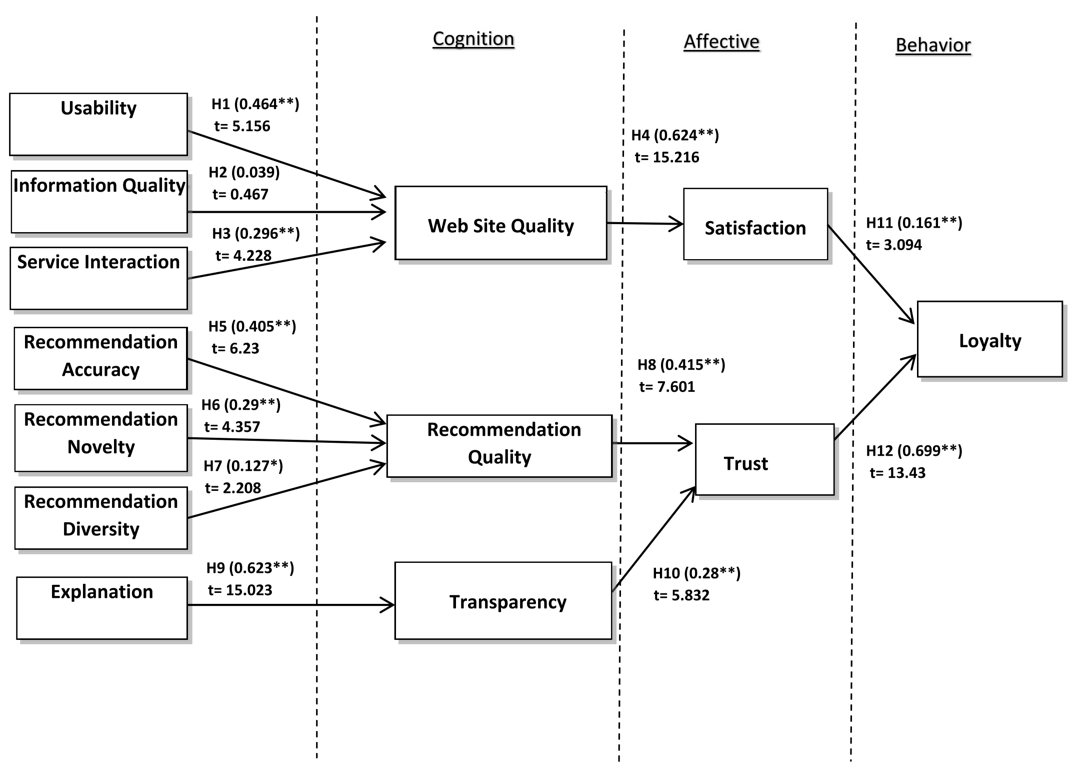

Fig. 2. Final loyalty model for E-commerce recommender systems.

Table 7
Hypotheses testing for the Main Study (Path coefficient).

Hypothesis	Relationship	β	Standard Deviation (STDEV)	t-value	p-value	
H1	USAB - > WEBQ	0.464	0.09	5.156	0	Supported**
H2	INFOR - > WEBQ	0.039	0.084	0.467	0.64	Not supported
H3	SERV - > WEBQ	0.296	0.07	4.228	0	Supported**
H4	WEBQ - > SATIS	0.624	0.041	15.216	0	Supported**
H5	ACU - > RQ	0.405	0.065	6.23	0	Supported**
H6	NOV - > RQ	0.29	0.067	4.357	0	Supported**
H7	DIV - > RQ	0.127	0.057	2.208	0.027	Supported*
H8	RQ - > TRUST	0.415	0.055	7.601	0	Supported**
H9	EXP - > TRANS	0.623	0.041	15.023	0	Supported**
H10	TRANS - > TRUST	0.28	0.048	5.832	0	Supported**
H11	SATIS - > LO	0.161	0.052	3.094	0.002	Supported**
H12	TRUST - > LO	0.699	0.052	13.43	0	Supported**

Significant at P** =< 0.01, P*< 0.05.

Table 8
R-squares of dependent variables.

Dep. Variables	Notation	R-Square
Loyalty	LO	0.673
Recommendation Quality	RQ	0.457
Satisfaction	SATIS	0.389
Transparency	TRANS	0.388
Trust	TRUST	0.339
Website Quality	WEBQ	0.557

Table 9
Effect size (f^2).

Relation Paths	Value	Effect
USAB - > WEBQ	0.168	Medium
INFOR - > WEBQ	0.001	No Effect
SERV - > WEBQ	0.067	Small
WEBQ - > SATIS	0.636	Large
ACU - > RQ	0.166	Medium
NOV - > RQ	0.124	Small
DIV - > RQ	0.02	Small
RQ - > TRUST	0.223	Medium
EXP - > TRANS	0.634	Large
TRANS - > TRUST	0.102	Small
SATIS - > LO	0.04	Small
TRUST - > LO	0.757	Large

Table 10
Construct cross-validated redundancy (Q^2).

	SSO	SSE	Q^2 (=1-SSE/SSO)
ACU	900	900	
DIV	900	900	
EXP	900	900	
INFOR	2100.00	2100.00	
LO	900	445.726	0.505
NOV	900	900	
RQ	1800.00	1367.78	0.24
SATIS	1800.00	1389.31	0.228
SERV	2100.00	2100.00	
TRANS	900	684.072	0.24
TRUST	1500.00	1130.21	0.247
USAB	2400.00	2400.00	
WEBQ	900	546.692	0.393

adoption theories have focused on the cognitive dimension to frame users' attitudes [52,53], most of the studies investigated user behavior in organizational settings, without the integration of hedonic dimensions [105]. Hence, our research differs in adopting an individual setting, where customers are seeking e-commerce recommender systems' assistance for their personal needs, and in which both utilitarian and hedonic dimensions are important to users' overall evaluation and continuance decisions.

The impacts of recommendation quality in promoting trust in a recommender system had been proven in previous studies [10], as asserted by our research. However, different quality factors have different (and significant) effects on the quality of the recommendations. The results of our study indicate that diversity has small effect size as a quality measure for recommendations. This can be explained by a simple justification; as users use the e-commerce recommender system to overcome the information overload problem and to make a purchase decision, diverse items might conflict with this purpose. Female users in our study appreciated accurate and surprisingly novel recommendations more than diverse recommendations. McGinty and Smyth [106] indicated that the impact of diverse items in increasing recommendation efficiency is not guaranteed in each recommendation list. This result highlights the need for more research in this area.

The quality of the website that hosts the recommender system proved to positively affect users' satisfaction towards recommendation agents. The constructs that we adopted from WebQual model have different effects on the quality of the website. Notably, the quality of the information does not have a significant effect on the users' perceived quality of the website. This result agrees with previous research by Nilashi et al. [10]; in which website quality factors have different levels of importance, depending on the domain or on the system under study. Other studies have rejected the hypothesis of the impact of the quality of information on user satisfaction regarding the design of the system [107], or have done so owing to the availability of the information outside the system [108].

7.2. Practical and managerial implications

This work tries to fill a gap in the research field of recommendation engines, and aims to interpret the aspects that promote user loyalty towards recommendation agents in e-commerce websites. A deep search in the literature motivated us to hypothesize the intermediating effects of consumer satisfaction and trust on the perceived system quality and consumer loyalty in the recommender system context, which had been confirmed in the literature of e-commerce research [39,109,110,118]. In the e-commerce marketing context, loyalty is measured by the collection of behavioral data. such as the purchase rate and purchase size, with regard to the ease of collection of such data [118]. However, this data might provide incorrect measurements regarding true loyalty [111]. This has encouraged us to explore users' subjective measures of loyalty towards recommendation agents. Following the previous research on recommender systems, our model confirmed the effects of trust and satisfaction on customer loyalty towards recommender systems. Our research also proves that both hedonic and utilitarian beliefs have an influence on a user's continuous intention to use the system. Service providers often assume that system quality relies on objective aspects, as reflected by explicit measures of the utilitarian dimensions of the system [77]. However, users' subjective perceptions of quality contain emotional elements that influences their behavior.

The benefits of utilizing recommendation agents in e-commerce websites have been investigated extensively in the literature [8,10,11]. Our study investigates the factors that have significant effects on loyalty formation towards e-commerce recommender system merchants. The results of the study provided substantial additional proof of the potential benefits of trust and satisfaction insofar as user loyalty towards recommendations agents, through the definitions and inspection of the lower-level constructs, and the use of a suitable instrument to measure them. The results of this study illustrated valuable outcomes, which indicate that improving consumer satisfaction and trust will improve consumer loyalty towards recommendations agents. This will then be reflected in merchants' increased earnings, in a stable manner. Thus, this longstanding relationship can be emphasized as an iterative loop between the recommender agents and customers, in which the customers continue to use the system over time, become more loyal to the system, and continue providing their preferences regarding items to the system, thereby facilitating a more productive user experience.

7.3. Limitations and future work

The results of the study have highlighted some important implications and future research directions, which can be summarized as follows.

i. There is a need to design experiments for user evaluations carefully with respect to different algorithms, different domains, and different aspects of user perceptions of the quality of recommender systems, such as diversity, familiarity, and novelty.
ii. The trade-offs between different quality factors must be formulated and balanced carefully in each user experiment to obtain credible and trustworthy results. Many quality factors might be in conflict. For example, the recommendation coverage and/or diversity might conflict with the accuracy.
ii. Usually, the recommender system is part of another system, such as a commercial website. Hence, there is a need to investigate the interface design of the website hosting the recommender system. More research is needed on users' evaluations of the ordering of the recommendations list, with respect to different quality aspects such as familiarity, diversity, novelty, and transparency.
iv. More study is required to compare the impacts of different recommendation approaches on user behavior, such as purchase behavior and loyalty. We could only find one study that examined the effect of recommendation quality on customer loyalty [11]. Future research studies could investigate the impacts of changing characteristics of the recommended products on users' decisions, such as in the context of user satisfaction and persuasion.
v. There is a need to focus on user interactions with the recommender system. The interaction with the system must be designed and evaluated carefully to reflect the goals of the system under study.

However, this research has some limitations regrading data distribution and collection. Only one e-commerce platform was considered for the evaluation. Although we tried to reach a wide range of respondents, the response rate was relatively low. We could only distribute the questionnaire among university students from one university in Saudi Arabia, which might affect the generalizability of this research to other communities. The response rate among male students was too low, so we only considered female respondents in this study. Future research can be conducted to investigate the impacts of quality factors from male and female perspectives. It can be anticipated that different results can be obtained from a male-dominated sample. In addition, recommended items generally entail two types of products: experiences, and search-characteristic products. Users' perception of each type differs in regards to different quality aspects. An extended study can be conducted on users' perceptions of different quality factors, with respect to each type of recommended product.

CRediT authorship contribution statement

Rabab Ali Abumalloh: Investigation, Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Othman Ibrahim:** Writing - original draft, Writing - review & editing. **Mehrbakhsh Nilashi:** Investigation, Conceptualization, Validation, Methodology, Writing - review & editing.

Appendix

Table A1
Loyalty in Previous Literature

Author	Context	Sample	Other Dimensions Measured	Direct antecedents	Theoretical Background
Eid [21]	E-commerce	235 college students and employers	- Perceived Privacy - User Interface Quality - Perceived Security - Information Quality	- Satisfaction - Trust	- Technology Acceptance Model (TAM) - The theory of reasoned action (TRA) - Expectation-Confirmation Theory (ECT)
Safa & Ismail [39]	E-commerce	254 customers of online markets with previous e-shopping experience	- Customer factors - Organizational factors - Technology factors	- Satisfaction - Trust	- Technology Acceptance Model - Least effort theory
Yoon et al. [11]	Recommender systems	251 college students	- Recommendation Quality - Recommendation Agent Type	- Satisfaction	- Cognition-Affective-Behavior Theory (C–A–B) - The theory of interpersonal similarity - Theory of human information processing
Luarn & Lin [41]	E-services	180 individuals	–	- Perceived value - Satisfaction - Commitment - Trust	The antecedents of e-loyalty
		197 customers of e-commerce	–	- Satisfaction	The antecedents of e-loyalty

(continued on next page)

Table A1 (*continued*)

Author	Context	Sample	Other Dimensions Measured	Direct antecedents	Theoretical Background
Janita & Miranda [112]	Business-to-business (B2B) e-commerce			- Value - Image - Quality	
Safa & Solms [26]	E-commerce	265 customers of online companies with previous e-shopping experience	- Security - Convenience - Reliable Payment System - Benefits - Clear Shopping Process - Enjoyment - Benevolence	- E-trust - E-satisfaction	- Cognition-Affective-Behavior Theory
Chang [40]	Mobile Application Commerce	320 users of mobile applications	- Price Value for Money - Emotional Value - Performance/Quality Value - Social Value	- Perceived Value - Satisfaction	The antecedents of e-loyalty
Cyr [28]	- E-commerce	571 individuals	- Information Design - Navigation Design - Visual Design	- Satisfaction - Trust	The antecedents of e-loyalty
Elkhani et al. [29]	- E-ticketing	357 online customers	- System Disconfirmation - Information Disconfirmation - Service Disconfirmation	- E-satisfaction	- Marketing mix 4Ps - Expectancy Disconfirmation Theory - E-ServQual
Zehir et al. [113]	E-commerce	645 individuals	- Fulfillment - Efficiency - Privacy - System availability	- Perceived Value	- E-Service Quality
Nadeem et al. [38]	- E-tailors' websites and social media	288 customers with previous e-shopping experience	- Service Quality - Peer Recommendations - E-Shopping via Facebook	- Trust - Attitudes towards e-tailor	The antecedents of e-loyalty
Setó-Pamies [89]	Retail travel agency sector	400 individuals who with previous usage experience	Quality Service	- Satisfaction - Trust	- ServQual
Chiou [54]	- Internet Service Providers	408 users	- Attributive Service	- Future ISP Expectancy - Satisfaction - Perceived Value - Perceived Trust	- Cognition-Affective-Behavior Theory
Cui & Lai [114]	- Online Auctions	449 bidders on the website	- Product diversity - Effectiveness of the bidding agent - Network effect - Effectiveness of the WTI function	- Perceived bidding enjoyment - Perceived bidding utility	- S–O–R model
Lin & Wang [30]	M-commerce	255 college students	–	- Satisfaction - Perceived Value - Trust - Habit	- Theory of Reasoned Action
[109]	B2C e-marketplaces	227 individuals with previous usage experience	- Benevolence - Competence - Integrity - Purchase Intention	- Trust in Intermediary - Trust in Seller	- The antecedents of trust
Hsu et al. [115]	Online group-buying	253 customers with previous e-shopping experience	- Trust in Sellers - Reputation of Website - Trust in Website - Reputation of Seller - Perceived Size of Seller - Perceived Size of Website	- Perceived Quality of Sellers - Satisfaction with Website - Satisfaction with Sellers	- IS Success Model - Determinants of Repurchase Intention

Table A2
The Questionnaire Items

Construct	Item	References
Recommendation Quality	1. The recommender system suggestions were helpful	[11,65]
	2. The recommender system suggestions were relevant	
	3. I became interested in the product after it was suggested by the website	
	4. I liked the items suggested by the website	
	5. The website suggested the kinds of items I like	
	6. I feel that the item suggestions helped me decide what to buy	
Recommendation Accuracy	7. The items recommended to me matched my interests	[10]
	8. The recommender gave me good suggestions	[8]
	9. I am not interested in the items recommended to me (reverse scale)	[8]
Recommendation Novelty	10. The items recommended to me are novel and interesting	[8]
	11. The recommender system helped me discover new items	[10]
	12. I could not find new items through the recommender (reverse scale)	[8]

(continued on next page)

Table A2 (*continued*)

Construct	Item	References
Recommendation Diversity	13. The items recommended to me are diverse	[8]
	14. The items recommended to me are similar to each other	[8]
	15. The items recommended to me are of various kinds	[10]
Explanation	16. The recommender explains why products are recommended to me	[8,10]
	17. When interacting with the recommender system, I felt I have been involved in its recommendation process	[10]
	18. This recommender system educates me about the process used for generating a recommendation, so that I could better understand the strengths and limitations of the system	[10]
Recommendation Transparency	19. I understand why the items were recommended to me	[8,10]
	20. I understand why the items were returned through the explanations in the interface	[8]
	21. The explanation facilities helped increase my acceptance of the recommendations made by the system.	[10]
Website Quality	22. My overall evaluation of the features of this website is very high	[10]
	23. The quality of this Web site meets my expectations	
	24. The Web site offered unique features to me that are different from other retail Web sites	
Web Site Quality: Usability	25. I find the website easy to learn to operate	[80]
	26. My interaction with the website is clear and understandable	
	27. I find the website easy to navigate	
	28. I find the website easy to use	
	29. The website has an attractive appearance	
	30. The website design is appropriate to the type of use	
	31. The website conveys a sense of competency	
	32. The website creates a positive experience for me	
Web Site Quality: Information	33. The website provides accurate information	[80]
	34. The website provides believable information	
	35. The website provides timely information	
	36. The website provides relevant information	
	37. The website provides easy to understand information	
	38. The website provides information at the right level of detail	
	39. The website presents the information in an appropriate format	
Web Site Quality: Service	40. The website has a good reputation	[80]
	41. It feels safe to complete transactions through the website	
	42. My personal information feels secure	
	43. The website creates a sense of personalization	
	44. The website conveys a sense of community	
	45. The website makes it easy to communicate with the organization	
	46. I feel confident that goods/services will be delivered as promised	
Satisfaction	47. Overall, I am satisfied with the recommender	[116]
	48. My overall satisfaction with the interface is high	[116]
	49. I am satisfied with my decision to purchase from this web site	[116]
	50. If I had to purchase again, I would feel differently about buying from this web site	[116]
	51. My choice to purchase from this web site was a wise one	[116]
	52. I regret my decision to buy from this web site	[37]
	53. I think I did the right thing by buying from this web site	[116]
	54. I am unhappy that I purchased from this web site	[116]
Trust	55. The recommender system can be trusted	[10]
	56. I feel that this recommender system is trustworthy	[93]
	57. This recommender system can be counted on to successfully complete purchase transactions	[37]
	58. I can trust the performance of this recommender system to be good	[37]
	59. This recommender system is reliable for my online shopping	[37]
Loyalty	60. It is likely that I will return to this recommender system	[116]
	61. I do recommend that others use the recommender system services	
	62. My preference for the recommender system would not willingly change	

Table A3
Loadings and Cross-Loadings for the Main Study

	ACU	DIV	EXP	LO	NOV	RQ	SATIS	SERV	TRANS	TRUST	USAB	WEBQ
E1	0.22	0.193	0.755	0.239	0.358	0.262	0.275	0.206	0.448	0.299	0.262	0.225
E2	0.314	0.335	0.789	0.39	0.39	0.471	0.35	0.304	0.418	0.387	0.371	0.31
E3	0.325	0.285	0.86	0.396	0.546	0.383	0.363	0.375	0.603	0.34	0.421	0.324
L-1	0.497	0.375	0.393	0.9	0.425	0.46	0.674	0.59	0.413	0.741	0.616	0.584
L-2	0.471	0.357	0.4	0.931	0.422	0.467	0.573	0.609	0.391	0.764	0.597	0.549
L-3	0.46	0.386	0.354	0.848	0.365	0.399	0.489	0.461	0.363	0.668	0.515	0.519
RA1	0.877	0.583	0.334	0.479	0.351	0.501	0.519	0.555	0.352	0.44	0.562	0.746
RA2	0.886	0.556	0.287	0.439	0.414	0.535	0.558	0.564	0.414	0.464	0.561	0.756
RA3RS	0.879	0.528	0.328	0.489	0.388	0.575	0.512	0.528	0.331	0.488	0.564	0.723
RD1	0.535	0.82	0.29	0.331	0.238	0.42	0.347	0.352	0.226	0.299	0.417	0.487
RD2RS	0.503	0.817	0.202	0.349	0.295	0.36	0.416	0.426	0.238	0.32	0.356	0.459
RD3	0.481	0.778	0.314	0.325	0.304	0.379	0.351	0.344	0.29	0.319	0.419	0.396
RN1	0.385	0.287	0.424	0.429	0.854	0.455	0.403	0.439	0.659	0.405	0.39	0.474
RN2	0.338	0.259	0.45	0.365	0.866	0.419	0.307	0.352	0.702	0.327	0.358	0.38
RN3RS	0.371	0.318	0.51	0.338	0.785	0.403	0.363	0.365	0.659	0.342	0.349	0.361
RQ1	0.496	0.403	0.332	0.418	0.402	0.774	0.455	0.445	0.334	0.478	0.446	0.474
RQ2	0.485	0.401	0.349	0.432	0.43	0.781	0.397	0.407	0.325	0.437	0.433	0.456
RQ3	0.425	0.259	0.264	0.276	0.262	0.67	0.287	0.285	0.16	0.313	0.266	0.311

(*continued on next page*)

Table A3 (*continued*)

	ACU	DIV	EXP	LO	NOV	RQ	SATIS	SERV	TRANS	TRUST	USAB	WEBQ
RQ4	0.417	0.352	0.326	0.355	0.389	0.768	0.279	0.281	0.256	0.353	0.308	0.365
RQ5	0.456	0.36	0.375	0.365	0.431	0.749	0.347	0.399	0.303	0.332	0.371	0.392
RQ6	0.48	0.38	0.42	0.374	0.371	0.773	0.391	0.399	0.304	0.416	0.424	0.412
S-1	0.538	0.41	0.426	0.538	0.392	0.43	0.827	0.591	0.422	0.631	0.608	0.545
S-2	0.473	0.332	0.303	0.439	0.291	0.369	0.784	0.525	0.271	0.531	0.603	0.451
S-3	0.522	0.4	0.369	0.569	0.385	0.422	0.871	0.657	0.396	0.63	0.648	0.567
S-4RS	0.337	0.287	0.331	0.412	0.237	0.286	0.67	0.379	0.31	0.363	0.41	0.316
S-5	0.522	0.379	0.271	0.537	0.369	0.413	0.834	0.601	0.387	0.545	0.567	0.553
S-7	0.454	0.368	0.276	0.594	0.348	0.369	0.781	0.622	0.333	0.612	0.563	0.5
T-1	0.483	0.337	0.348	0.713	0.358	0.463	0.645	0.62	0.369	0.873	0.584	0.57
T-2	0.427	0.368	0.378	0.668	0.348	0.42	0.604	0.568	0.372	0.838	0.552	0.498
T-3	0.455	0.328	0.373	0.692	0.402	0.438	0.62	0.559	0.415	0.894	0.573	0.558
T-4	0.47	0.334	0.351	0.714	0.382	0.48	0.637	0.602	0.392	0.914	0.606	0.566
T-5	0.499	0.348	0.413	0.797	0.409	0.498	0.605	0.604	0.387	0.901	0.618	0.591
TRA1	0.358	0.231	0.428	0.386	0.659	0.319	0.383	0.373	0.805	0.377	0.346	0.439
TRA2	0.319	0.239	0.48	0.35	0.695	0.311	0.311	0.334	0.852	0.325	0.36	0.371
TRA3	0.347	0.292	0.609	0.347	0.644	0.309	0.404	0.386	0.818	0.377	0.38	0.355
WQ1	0.741	0.497	0.327	0.54	0.392	0.448	0.548	0.558	0.401	0.52	0.607	0.875
WQ2	0.723	0.492	0.284	0.51	0.45	0.451	0.567	0.613	0.44	0.551	0.621	0.878
WQ3	0.725	0.459	0.321	0.555	0.423	0.502	0.506	0.584	0.372	0.567	0.635	0.846
WQS-1	0.545	0.423	0.27	0.563	0.325	0.424	0.631	0.81	0.344	0.596	0.648	0.614
WQS-2	0.536	0.446	0.33	0.542	0.445	0.415	0.615	0.875	0.429	0.608	0.658	0.603
WQS-3	0.497	0.408	0.31	0.48	0.377	0.389	0.561	0.86	0.336	0.507	0.6	0.519
WQS-4	0.506	0.345	0.29	0.472	0.354	0.357	0.57	0.847	0.308	0.523	0.575	0.531
WQS-5	0.446	0.302	0.331	0.481	0.357	0.418	0.448	0.657	0.335	0.448	0.525	0.476
WQS-6	0.482	0.338	0.264	0.46	0.433	0.385	0.57	0.771	0.429	0.497	0.597	0.506
WQS-7	0.479	0.317	0.322	0.497	0.316	0.402	0.617	0.788	0.313	0.556	0.616	0.529
WQU-1	0.465	0.323	0.377	0.544	0.341	0.352	0.582	0.568	0.432	0.528	0.76	0.511
WQU-2	0.495	0.349	0.373	0.492	0.355	0.425	0.578	0.598	0.386	0.534	0.741	0.55
WQU-3	0.529	0.449	0.325	0.52	0.312	0.341	0.588	0.631	0.348	0.526	0.832	0.6
WQU-4	0.518	0.406	0.354	0.516	0.314	0.409	0.64	0.642	0.363	0.582	0.842	0.569
WQU-5	0.43	0.383	0.355	0.417	0.291	0.359	0.477	0.488	0.247	0.451	0.741	0.485
WQU-6	0.476	0.327	0.292	0.414	0.323	0.369	0.528	0.588	0.275	0.447	0.795	0.538
WQU-7	0.499	0.404	0.338	0.519	0.368	0.401	0.515	0.565	0.337	0.499	0.769	0.57
WQU-8	0.565	0.44	0.369	0.608	0.427	0.489	0.568	0.616	0.364	0.577	0.777	0.64

References

[1] Long-Yi Lin, Ching-Yuh Lu, "The influence of corporate image, relationship marketing, and trust on purchase intention: the moderating effects of word-of-mouth, Tourism Rev. 65 (3) (2010) 16–34.

[2] Guy H. Gessner, Coral R. Snodgrass, Designing E-commerce cross-border distribution networks for small and medium-size enterprises incorporating Canadian and U.S. Trade incentive programs, Research in Transportation Business & Management 16 (2015) 84–94.

[3] Tony Ahn, Seewon Ryu, Ingoo Han, The impact of the online and offline features on the user acceptance of internet shopping malls, in: Electronic Commerce Research and Applications, 2004, pp. 405–420.

[4] J Ben Schafer, Joseph A. Konstan, John Riedl, E-commerce recommendation applications, in: Applications of Data Mining to Electronic Commerce, Springer US, Boston, MA, 2001, pp. 115–153.

[5] Zhihai Yang, Lin Xu, Zhongmin Cai, Zongben Xu, Re-scale AdaBoost for attack detection in collaborative filtering recommender systems, Knowl. Base Syst. 100 (2016) 74–88.

[6] Muhammad Aljukhadar, Sylvain Senecal, Charles-Etienne Daoust, Information overload and usage of recommendations, in: Proceedings of the ACM RecSys 2010 Workshop on User-Centric Evaluation of Recommender Systems and Their Interfaces (UCERSTI), CEUR-WS. Org, 2010, pp. 26–33.

[7] Jonathan L. Herlocker, Joseph A. Konstan, Loren G. Terveen, John T. Riedl, Evaluating collaborative filtering recommender systems, ACM Trans. Inf. Syst. 22 (1) (2004) 5–53.

[8] Pearl Pu, Li Chen, Rong Hu, A user-centric evaluation framework for recommender systems, in: Proceedings of the Fifth ACM Conference on Recommender Systems, ACM, 2011, pp. 157–164.

[9] Xin Wayne Zhao, et al., We know what you want to buy, in: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '14, ACM Press, New York, New York, USA, 2014, pp. 1935–1944.

[10] Mehrbakhsh Nilashi, et al., Recommendation quality, transparency, and website quality for trust-building in recommendation agents, Electron. Commer. Res. Appl. 19 (2016) 70–84.

[11] Victoria Y. Yoon, R. Eric Hostler, Zhiling Guo, Tor Guimaraes, Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty, Decis. Support Syst. 55 (4) (2013) 883–893.

[12] da Silva, Edjalma Queiroz, G. Celso, Camilo-Junior, Luiz Mario L. Pascoal, Thierson C. Rosa, An evolutionary approach for combining results of recommender systems techniques based on collaborative filtering, Expert Syst. Appl. 53 (2016) 204–218.

[13] Feng Zhang, et al., Fast algorithms to evaluate collaborative filtering recommender systems, Knowl. Base Syst. 96 (2016) 96–103.

[14] Kem Z.K. Zhang, Morad Benyoucef, Sesia J. Zhao, Building brand loyalty in social commerce: the case of brand microblogs, Electron. Commer. Res. Appl. 15 (2016) 14–25.

[15] Bart P. Knijnenburg, et al., Explaining the user experience of recommender systems, User Model. User-Adapted Interact. 22 (4–5) (2012) 441–504.

[16] Viswanath Venkatesh, Y. James, L. Thong, Xin Xu, Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology, MIS Q. 36 (1) (2012) 157–178.

[17] Mohd Syuhaidi Abu Bakar, Rosmiza Bidin, Technology acceptance and purchase intention towards movie mobile advertising among youth in Malaysia, Procedia - Social and Behavioral Sciences 130 (2014) 558–567.

[18] See Siew Sin, Khalil Md Nor, M. Ameen, Al-Agaga, "Factors affecting Malaysian Young consumers' online purchase intention in social media websites, Procedia - Social and Behavioral Sciences 40 (2012) 326–333.

[19] Ali Tarhini, Nalin Asanka Gamagedara Arachchilage, Ra'ed Masa'deh, Muhammad Sharif Abbasi, A critical review of theories and models of technology adoption and acceptance in information system research, Int. J. Technol. Diffusion (IJTD) 6 (4) (2015) 58–77.

[20] Ahmad Mansouri, et al., "The impact assessment of the quality factors of different brands of machine-made carpet in increasing costumer's satisfaction (A case study: machine –made carpet produced in boukan), J. Basic. Appl. Sci. Res 2 (6) (2012) 6128–6132.

[21] Mustafa I. Eid, "Determinants of E-commerce customer satisfaction, trust, and loyalty in Saudi Arabia" ed. Intergovernmental panel on climate change, J. Electron. Commer. Res. 12 (1) (2011) 78–93.

[22] Dietmar Jannach, Ingrid Nunes, Michael Jugovac, Interacting with recommender systems, in: Proceedings of the 22nd International Conference on Intelligent User Interfaces Companion - IUI '17 Companion, ACM Press, New York, New York, USA, 2017, pp. 25–27.

[23] France Bélanger, Lemuria Carter, Trust and risk in E-government adoption, J. Strat. Inf. Syst. 17 (2) (2008) 165–176.

[24] Chao-Min Chiu, Hua-Yang Lin, Szu-Yuan Sun, Meng-Hsiang Hsu, "Understanding customers' loyalty intentions towards online shopping: an integration of technology acceptance model and fairness theory, Behav. Inf. Technol. 28 (4) (2009) 347–360.

[25] Aysel Erciş, Sevtap Ünal, F. Burcu Candan, Hatice Yıldırım, The effect of brand satisfaction, trust and brand commitment on loyalty and repurchase intentions, Procedia - Social and Behavioral Sciences 58 (2012) 1395–1404.

[26] Nader S. Safa, Rossouw Von Solms, Customers repurchase intention formation in E-commerce, SA Journal of Information Management 18 (1) (2016) 1–9.
[27] Srinivasan, S. Srini, et al., Customer loyalty in E-commerce: an exploration of its antecedents and consequences, J. Retailing 78 (1) (2002) 41–50.
[28] Dianne Cyr, Modeling web site design across cultures: relationships to trust, satisfaction, and E-loyalty, J. Manag. Inf. Syst. 24 (4) (2008) 47–72.
[29] Naeimeh Elkhani, Sheida Soltani, Mir Hadi Moazen Jamshidi, Examining a hybrid model for E-satisfaction and e-loyalty to e-ticketing on airline websites, J. Air Transport. Manag. 37 (2014) 36–44.
[30] Hsin-Hui Lin, Yi-Shun Wang, An examination of the determinants of customer loyalty in mobile commerce contexts, Inf. Manag. 43 (3) (2006) 271–282.
[31] Giang Tue Trinh, Zachary William Anesbury, Carl Driesener, Has behavioural loyalty to online supermarkets declined? Australas. Market J. 25 (4) (2017) 326–333.
[32] Timmy H. Tseng, Crystal T. Lee, Facilitation of consumer loyalty toward branded applications: the dual-route perspective, Telematics Inf. 35 (5) (2018) 1297–1309.
[33] Jengchung Victor Chen, David C. Yen, Wannasri Pornpriphet, E Widjaja Andree, E-Commerce web site loyalty: a cross cultural comparison, Inf. Syst. Front 17 (6) (2015) 1283–1299.
[34] N.M. Manzuma-Ndaaba, Y. Harada, A.R. Romle, A.S. Shamsudin, Cognitive, affective and conative loyalty in higher education marketing: proposed model for emerging destinations, Int. Rev. Manag. Market. 6 (4S) (2016) 168–175.
[35] Rolph E. Anderson, Srini S. Srinivasan, E-Satisfaction and e-loyalty: a contingency framework, Psychol. Market. 20 (2) (2003) 123–138.
[36] Aikaterini C. Valvi, Konstantinos C. Fragkos, Critical review of the E-loyalty literature: a purchase-centred framework, Electron. Commer. Res. 12 (3) (2012) 331–378.
[37] Rolph E. Anderson, Srinivasan Swaminathan, Customer satisfaction and loyalty in E-markets: a PLS path modeling approach, J. Market. Theor. Pract. 19 (2) (2011) 221–234.
[38] Waqar Nadeem, Daniela Andreini, Jari Salo, Tommi Laukkanen, Engaging consumers online through websites and social media: a gender study of Italian generation Y clothing consumers, Int. J. Inf. Manag. 35 (4) (2015) 432–442.
[39] Nader Sohrabi Safa, Maizatul Akmar Ismail, A customer loyalty formation model in electronic commerce, Econ. Modell. 35 (2013) 559–564.
[40] Chiao-Chen Chang, Exploring mobile application customer loyalty: the moderating effect of use contexts, Telecommun. Pol. 39 (8) (2015) 678–690.
[41] Pin Luarn, Hsin Hui Lin, A customer loyalty model for E-service context, J. Electron. Commer. Res. 4 (4) (2003) 156–167.
[42] G. Lenzini, Y. van Houten, W. Huijsen, M. Melenhorst, Shall I trust a recommendation? Towards an evaluation of the trustworthiness of recommender sites, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, 2010, pp. 121–128.
[43] Eric Yeboah Asiamah, Simon Gyasi Nimako, Daniel M. Quaye, Samuel Buame, Implicit and explicit loyalty: the role of satisfaction, trust and brand image in mobile telecommunication industry, Int. J. Bus. Emerg. Mark. 8 (1) (2016) 94.
[44] John O'Donovan, Barry Smyth, Trust in recommender systems, in: Proceedings of the 10th International Conference on Intelligent User Interfaces, ACM, 2005, pp. 167–174.
[45] Sean M. McNee, John Riedl, Joseph A. Konstan, Being accurate is not enough, in: CHI '06 Extended Abstracts on Human Factors in Computing Systems - CHI EA '06, ACM Press, New York, New York, USA, 2006, p. 1097.
[46] Mohammed Z. Al-Taie, Seifedine Kadry, Visualization of explanations in recommender systems, Journal of Advanced Management Science 2 (1) (2014) 140–144.
[47] Li Chen, Feng Wang, Explaining recommendations based on feature sentiments in product reviews, in: Proceedings of the 22nd International Conference on Intelligent User Interfaces - IUI '17, ACM Press, New York, New York, USA, 2017, pp. 17–28.
[48] Richard L. Oliver, Whence consumer loyalty? J. Market. 63 (4_suppl1) (1999) 33–44.
[49] I. Chan Fang, Shih Chieh Fang, Factors affecting consumer stickiness to continue using mobile applications, Int. J. Mobile Commun. 14 (5) (2016) 431–453.
[50] Kuo-Lun Hsiao, Chia-Chen Chen, What drives in-app purchase intention for mobile games? An examination of perceived values and loyalty, Electron. Commer. Res. Appl. 16 (2016) 18–29.
[51] Sherrie Y.X. Komiak, Izak Benbasat, The effects of personalization and familiarity on trust and adoption of recommendation agents, MIS Q. 30 (4) (2006) 941–960.
[52] Venkatesh, Morris, Davis, Davis, User acceptance of information technology: toward a unified view, MIS Q. 27 (3) (2003) 425.
[53] Fred D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. 13 (3) (1989) 319–340.
[54] Jyh-Shen Chiou, "The antecedents of consumers' loyalty toward internet service providers, Inf. Manag. 41 (6) (2004) 685–695.
[55] Shun Yin Lam, Venkatesh Shankar, M. Krishna Erramilli, Bvsan Murthy, Customer value, satisfaction, loyalty, and switching costs: an illustration from a business-to-business service context, Journai of the Academy of Marketiag Science 32 (3) (2004) 293–311.
[56] Alice H. Eagly, Shelly Chaiken, The Psychology of Attitudes, Harcourt Brace Jovanovich College Publishers, 1993.
[57] Richard P. Bagozzi, The self-regulation of attitudes, intentions, and behavior, Soc. Psychol. Q. 55 (2) (1992) 178.
[58] Richard S. Lazarus, Cognition and motivation in emotion, Am. Psychol. 46 (4) (1991) 352–367.
[59] Jeamok Kwon, Christine A. Vogt, "Identifying the role of cognitive, affective, and behavioral components in understanding residents' attitudes toward place marketing, J. Trav. Res. 49 (4) (2010) 423–435.
[60] Scott Taylor, Robin B. DiPietro, Kevin Kam Fung So, Increasing experiential value and relationship quality: an investigation of pop-up dining experiences, Int. J. Hospit. Manag. 74 (May) (2018) 45–56.
[61] Ching-Fu Chen, Sambath Phou, A closer look at destination: image, personality, relationship and loyalty, Tourism Manag. 36 (2013) 269–278.
[62] Paramaporn Thaichon, Thu Nguyen Quach, "The relationship between service quality, satisfaction, trust, value, commitment and loyalty of internet service providers' customers, Journal of Global Scholars of Marketing Science 25 (4) (2015) 295–313.
[63] Ido Liviatan, Yaacov Trope, Nira Liberman, "Interpersonal similarity as a social distance dimension: implications for perception of others' actions, J. Exp. Soc. Psychol. 44 (5) (2008) 1256–1269.
[64] Xiao, Benbasat, E-commerce product recommendation agents: use, characteristics, and impact, MIS Q. 31 (1) (2007) 137–209.
[65] R. Eric Hostler, et al., Assessing the impact of recommender agents on on-line consumer unplanned purchase behavior, Inf. Manag. 48 (8) (2011) 336–343.
[66] D Harrison Mcknight, Larry L. Cummings, Norman L. Chervany, InitialTrustAMR, Acad. Manag. Rev. 23 (3) (1998) 473–490.
[67] D. Harrison McKnight, Norman L. Chervany, What trust means in E-commerce customer relationships: an interdisciplinary conceptual typology, Int. J. Electron. Commer. 6 (2) (2001) 35–59.
[68] Pearl Pu, Li Chen, Trust-inspiring explanation interfaces for recommender systems, Knowl. Base Syst. 20 (6) (2007) 542–556.
[69] Alan D.J. Cooke, Sujan Harish, Sujan Mita, Barton A. Weitz, Marketing the unfamiliar: the role of context and item-specific information in electronic agent recommendations, J. Market. Res. 39 (4) (2002) 488–497.
[70] Jonathan L. Herlocker, Joseph A. Konstan, John Riedl, Explaining collaborative filtering recommendations, in: Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work - CSCW '00, ACM Press, New York, New York, USA, 2000, pp. 241–250.
[71] Weiquan Wang, Izak Benbasat, Recommendation agents for electronic commerce: effects of explanation facilities on trusting beliefs, J. Manag. Inf. Syst. 23 (4) (2007) 217–246.
[72] Hsin Hsin Chang, Su Wen Chen, The impact of online store environment cues on purchase intention: trust and perceived risk as a mediator, Online Inf. Rev. 32 (6) (2008) 818–841.
[73] Dr Shubham Goswami, Measuring customer satisfaction on webqual dimension for online banking: an empirical study, Paradigmi 17 (1–2) (2013) 25–36.
[74] Josua Tarigan, "User satisfaction using webqual instrument: a research on stock exchange of Thailand (set), Jurnal Akutansi dan Keuangan 10 (1) (2008) 34–47.
[75] Billy Bai, Rob Law, Ivan Wen, The impact of website quality on customer satisfaction and purchase intentions: evidence from Chinese online visitors, Int. J. Hospit. Manag. 27 (3) (2008) 391–402.
[76] Jasur Hasanov, Haliyana Khalid, The impact of website quality on online purchase intention of organic food in Malaysia: a WebQual model approach, Procedia Computer Science 72 (2015) 382–389.
[77] Björn Frank, Boris Herbas Torrico, Enkawa Takao, J. Shane, Schvaneveldt, Affect versus cognition in the chain from perceived quality to customer loyalty: the roles of product beliefs and experience, J. Retailing 90 (4) (2014) 567–586.
[78] Yi-Shun Wang, et al., Developing and validating a mobile catering app success model, Int. J. Hospit. Manag. 77 (April) (2019) 19–30.
[79] Rola Hengki, Analysis quality dino tour travel management website using WebQual 4.0, in: International Conference on Engineering and Technology Development (ICETD), 2014, pp. 98–105.
[80] S. Barnes, R. Vidgen, An integrative approach to the assessment of E-commerce quality: online book stores, J. Electron. Commer. Res. 3 (3) (2002) 114–127.
[81] Stuart Barnes, Richard Vidgen, WebQual: an exploration of web-site quality stuart, in: Proceedings of the Eight European Conference on Information System, Vienna, 2000, pp. 298–305.
[82] Marius Kaminskas, Derek Bridge, Diversity, serendipity, novelty, and coverage, ACM Transactions on Interactive Intelligent Systems 7 (1) (2016) 1–42.
[83] Dietmar Jannach, Lukas Lerche, Michael Jugovac, Item familiarity as a possible confounding factor in user-centric recommender systems evaluation, in: Icom, De Gruyter Oldenbourg., 2015, pp. 29–39.
[84] Kirsten Swearingen, Rashmi Sinha, Interaction design for recommender systems, Designing Interactive Systems 6 (12) (2002) 1–10.
[85] Rashmi Sinha, Kirsten Swearingen, The role of transparency in recommender systems, in: CHI 02 Extended Abstracts on Human Factors in Computing Systems CHI, vol. 2, 2002, p. 830.
[86] Nava Tintarev, Judith Masthoff, Explanations of recommendations, in: Proceedings of the 2007 ACM Conference on Recommender Systems, ACM, New York, New York, USA, 2007, p. 203.
[87] Mohammed Z. Al-Taie, Explanations in recommender systems: an overview, in: Proceedings of the 14th International Arab Conference on Information Technology, ACIT, Khartoum, Sudan, 2013.
[88] Mouzhi Ge, Carla Delgado-Battenfeld, Dietmar Jannach, User-perceived recommendation quality - factoring in the user interface, in: ACM RecSys, 2010, pp. 22–25.
[89] Dolors Setó-Pamies, Customer loyalty to service providers: examining the role of service quality, customer satisfaction and trust, Total Qual. Manag. Bus. Excel. 23 (11–12) (2012) 1257–1271.
[90] Li Chen, Pearl Pu, Interaction design guidelines on critiquing-based recommender systems, User Model. User-Adapted Interact. 19 (3) (2009) 167–206.

[91] Mark Kasunic, Designing an Effective Survey (No. Cmu/Sei-2005-Hb-004), Carnegie-Mellon Univ Pittsburgh Pa Software Engineering Inst, 2005.
[92] Yen-Yao Wang, Andy Luse, Anthony M. Townsend, Brian E. Mennecke, Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems, Inf. Syst. E Bus. Manag. 13 (4) (2015) 769–799.
[93] David Gefen, Customer loyalty in E-commerce, J. Assoc. Inf. Syst. Online 3 (1) (2002) 27–53.
[94] Gwo-Guang Lee, Hsiu-Fen Lin, "Customer perceptions of E-service quality in online shopping, Int. J. Retail Distrib. Manag. 33 (2) (2005) 161–176.
[95] Rita Walczuch, Henriette Lundgren, Psychological antecedents of institution-based consumer trust in e-retailing, Inf. Manag. 42 (1) (2004) 159–177.
[96] Chao Wen, Victor R. Prybutok, Chenyan Xu, An integrated model for customer online repurchase intention, J. Comput. Inf. Syst. 52 (1) (2011) 14–23.
[97] Thomas Kramer, The effect of measurement task transparency on preference construction and evaluations of personalized recommendations, J. Market. Res. 44 (2) (2007) 224–233.
[98] Nanda Kumar, Izak Benbasat, Research note: the influence of recommendations and consumer reviews on evaluations of websites, Inf. Syst. Res. 17 (4) (2006) 425–439.
[99] a. Ant Ozok, Quyin Fan, Anthony F. Norcio, Design guidelines for effective recommender system interfaces based on a usability criteria conceptual model: results from a college student population, Behav. Inf. Technol. 29 (1) (2010) 57–83.
[100] Chao Wen, Victor R. Prybutok, Charles Blankson, Jiaming Fang, The role of E-quality within the consumer decision making process, Int. J. Oper. Prod. Manag. 34 (12) (2014) 1506–1536.
[101] Joe Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt, 46 Sage Publications *A Primer on Partial Least Squares Structural Equation Modeling*, SAGE Publications Inc, Thousand Oaks, United States, 2013.
[102] Joe F. Hair, Christian M. Ringle, Marko Sarstedt, PLS-SEM: indeed a silver bullet, J. Market. Theor. Pract. 19 (2) (2011) 139–152.
[103] Jörg Henseler, Christian M. Ringle, Rudolf R. Sinkovics, The use of partial least squares path modeling in international marketing, Adv. Int. Market. 20 (2009) 277–319.
[104] Jacob Cohen, Statistical Power Analysis for the Behavioral Sciences, Routledge, 1988.
[105] Dan J. Kim, Yong I. Song, S.B. Braynov, H.R. Rao, A multidimensional trust formation model in B-to-C e-commerce: a conceptual framework and content analyses of academia/practitioner perspectives, Decis. Support Syst. 40 (2) (2005) 143–165.
[106] Lorraine McGinty, Barry Smyth, On the role of diversity in conversational recommender systems, in: International Conference on Case-Based Reasoning, Springer Berlin Heidelberg, 2003, pp. 276–290.
[107] Darmawan Napitupulu, Analysis of factors affecting the website quality (study case: XYZ university), Int. J. Adv. Sci. Eng. Inf. Technol. 7 (3) (2017) 792.
[108] Dyah Ayu Kusuma Wardani, Riskayanto, Analysis of information system quality and user acceptance on internet banking industry, Journal of Global Economics Wardani 7 (1) (2019) 1–8.
[109] Ilyoo B. Hong, Hwihyung Cho, The impact of consumer trust on attitudinal loyalty and purchase intentions in B2C E-marketplaces: intermediary trust vs. Seller trust, Int. J. Inf. Manag. 31 (5) (2011) 469–479.
[110] ShinYoung Hwang, Seongcheol Kim, Does MIM experience affect satisfaction with and loyalty toward O2O services? Comput. Hum. Behav. 82 (2018) (2018) 70–80.
[111] Lyle R. Wetsch, Trust, satisfaction and loyalty in customer relationship management: an application of justice theory, in: The Future of Relationship Marketing, The Haworth Press, Inc, 2013, pp. 29–42.
[112] M Soledad Janita, F Javier Miranda, The antecedents of client loyalty in business-to-business (B2B) electronic marketplaces, Ind. Market. Manag. 42 (5) (2013) 814–823.
[113] Cemal Zehir, Yasin Sehitoglu, Elif Narcikara, Songül Zehir, E-S-Quality, perceived value and loyalty intentions relationships in internet retailers, Procedia - Social and Behavioral Sciences 150 (2014) 1071–1079.
[114] Xiling Cui, Vincent S. Lai, E-Loyalty to online auction websites: a stimulus-organism-response model, in: Pacific Asia Conference on Information Systems, PACIS), 2013, p. 126.
[115] Meng Hsiang Hsu, Ming Chang Chun, Kuang Chu Kuo, Yi Jung Lee, Determinants of repurchase intention in online group-buying: the perspectives of DeLone & McLean is success model and trust, Comput. Hum. Behav. 36 (2014) 234–245.
[116] Richard L. Oliver, A cognitive model of the antecedents and consequences of satisfaction decisions, J. Market. Res. 17 (4) (1980) 460.
[117] Hair Jr., F. Joseph, G. Tomas, M. Hult, Christian Ringle, Marko Sarstedt, A primer on partial least squares structural equation modeling (PLS-SEM), Sage publications, 2016.
[118] L.R. Wetsch, Trust, satisfaction and loyalty in customer relationship management: an application of justice theory, J. Relationship Market. 4 (3-4) (2006) 29–42.
[119] E. Yeboah-Asiamah, D.M. Quaye, S.G. Nimako, The effects of lucky draw sales promotion on brand loyalty in mobile telecommunication industry. Afr, J. Econ. Manag. Stud. Vol. 8 (No. 1) (2016) 94–115.