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Advancing on weighted PLS-SEM in examining the trust-based recommendation system in pioneering product promotion effectiveness

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Abstract

The advancement in digital technologies has led to an explosive information phenomenon, particularly in Internet shopping. This paper attempts to examine the trust element in the current pervasive use of the recommendation system for product promotion effectiveness. Owing to the nature of high-volume online consumers and the nonexistence of the online consumer sampling frame, sampling weight adjustment approach was utilised for ensuring sample representativeness. Additionally, the responses collected were further analysed according to gender for a holistic understanding of the trust element. A cross-sectional quantitative research approach was adopted. Specifically, snowball sampling method was used to collect responses from online consumers. The findings revealed that benevolence, integrity, and competence trust are found to be positively associated with product promotion effectiveness. Competence trust recorded a large effect size followed by benevolence and integrity trust. Both male and female consumers shown different degrees of trust level. The findings provide practical implications for online merchants. They were suggested to focus on enhancing online consumers' trust level and capitalize on competence trust for effective product promotion. They should also recognize the gender differences in the trust level for product promotion effectiveness when they are promoting gender-based products and services.

Keywords Trust-based recommendation system · Product promotion effectiveness · Marketing · Sampling weights · Weighted PLS (WPLS) · MGA

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1 Introduction

Information technology systems have ever advanced in this new millennium and have provided convenience to our daily lives, be it personal or business. Much information is readily available at one' fingertips through the navigation of smart devices. Meanwhile, many business transactions have taken place beyond the brick-and-mortar setting. The development of the worldwide digital economy is driving the emergence of digital commerce worldwide, whereby it was reported that consumers spend approximately $3.46 trillion online in 2019 as compared to $2.93 trillion in 2018 (Young 2019). Clement (2019) forecasted that globally, over 2.14 billion people buy goods and services from online platforms, with 63% of shopping occasions in virtual stores.

Despite the significant growth of digital commerce that provides great convenience for consumers, the changes also pose several challenges, such as leaking personal information and data. This scenario will indirectly lead to an overload of information when consumers are flooded with excessive resources and information options (Dash et al. 2021; Matthes et al. 2020). To address this problem, retailers have begun to set up a recommendation system on their digital trading platforms to push products and services to consumers based on their potential needs, behaviour, preferences, etc. This approach allows retailers to improve product sales conversion rates while helping consumers look for the products they need and offer them more diversified products (Huo 2021; Hwangbo et al. 2018). In practice, the recommendation system can be grouped into a regular recommendation system and personalized recommendation system (Yun et al. 2018). More specifically, the typical recommendation system refers to the selection of some relevant offers based on the consumer's purchase history, while the personalized recommendation system is based on consumer buying habits and product characteristics (Nair and Gupta 2017).

In the domain of digital commerce, trust has gained a great deal of interest in research along with the increase in online transactions. Undoubtedly, the lacking of trust has been regarded as a serious obstacle to the adoption of digital commerce, and this is an important factor that distinguishes online buyers from non-buyers (Fatonah et al. 2020; Goh et al. 2020; Nguyen and Pervan 2020; Chang et al. 2013). Several disciplines, such as psychology, marketing, communication, and sociology have examined trust as a broad and elusive term (Bozic 2017; Oliveira et al. 2017). One of the most influential definitions was suggested by Moorman et al. (1993), which defined trust "as a willingness to rely on an exchange partner in whom one has confidence". A multitude of research has documented that confident consumers are often more loyal and engaged (Cheng et al. 2014, 2019; Coelho et al. 2018) and easier to accept new products (Rathore and Ilavarasan 2020). Furthermore, trust between retailers and consumers can also promote strong, quality and sustainable relations (Cham et al. 2020, 2021; Cui et al. 2020). Consequently, the examination on the effect of trust towards product promotion effectiveness has become a critical theoretical concern in the literature on the recommendation system. It is perceived that a trust-based recommendation system is critically important for the consumer to make a decision. Simultaneously, practitioners are urged to look into this trust-based recommendation system in order to compete rigorously in winning the sale.

In addition, previous research has highlighted the significant difference between men and women in terms of the buying process (Lim et al. 2019, 2021; San Martín and Jiménez 2011). Prakash and Flores (1985) argued that the subject of gender is often linked to cultural and social meanings that are associated with the development of a marketing strategies since male–female dichotomy has been regarded as the most fundamental dichotomy in the society at large. According to gender schema theory (Bem 1981), both male and female tend to use a different approach in the treatment of information, which causes a significant difference between them. In practice, gender information tends to be easily accessible and identifiable, which can be used as a valuable market segmentation tool (Oh et al. 2002; Vaidyanathan and Aggarwal 2020). While it is important to examine gender differences, few researches have been conducted to study how male and female behave differently in the perception of the information obtained from the recommendation system. For example, Garbarino and Strahilevitz (2004) pointed out that female consumers tend to value more towards the information receiving from a recommendation site in comparison the male counterpart. Previous work reported that female placed more emphasis on socialization compare to the male counterpart, so this segment of consumers (i.e. females) is more likely to disclose personal information with others and to change their behaviour in response to signals received from others (Eagly and Wood 1991; Brannon 2016). Thus, by examining the differences between male and female consumers in terms of their perception of trust towards the product or service recommended by the system in digital commerce, this study is perceived to offer beneficial insights to the body of knowledge.

2 Literature review

2.1 Recommendation systems

The internet has become an indispensable element in our daily lives, and it gets more significant with the adoption of the digital economy, digital marketing, and artificial intelligence along with machine learning. This development leads to a sharp increase in the volume of online information, and consumers are facing difficulty to identify every information available on the internet. This has caused the phenomenon of "information explosion''. Information explosion occurs when the overloading of information causes difficulty in handling and comprehending the high volume of online data. To curb this phenomenon, many platforms started to launch specific systems such as search interactive decision systems, engine, personalization, and recommendation systems in their websites to help consumers filter important information.

In addition to the above, recommendation systems are pervasive, and they are found in numerous online environments such as e-commerce, social networks, mobile applications, Internet advertisements, and other important areas that involve personal communications and transactions. Based on the extant literature, variety of terms are used such as "personalization", "interactive decision aid", "recommendation agent", and "recommender". Despite the identical term of "recommendation system", scholars have employed different definitions of means by such systems. For the current research, Li and Karahanna's (2015) definition is adopted because of its simplicity yet matching with the current research objectives to examine trust-based recommendation systems for product promotion effectiveness. According to Li and Karajamma (2015), recommendation systems refer to Web-based tools that tailor vendors' offerings to consumers based on their preferences. Technically, recommendation systems work by using communications networks and multicomponent analysis to recommend or predict suitable goods and services from the identified commercial products (Shaya et al. 2010). The recommendation systems used artificial intelligence (AI) to process objective and/or subjective goods and services information received from consumers or based on the inputs saved in the system. The systems' output comprise a set of goods and services that predict the consumers' preferences and what they are likely to be interested in. The recommendation systems capitalised AI elements to understand product responsiveness patterns and to address consumer problems. The objective product information is derived from the diagnostic instruments developed by AI algorithms. Data gathered is then communicated to the next level of data processing portions of the findings through Internet connection. Subsequently, the outcomes of the data processing from the recommendation systems are then presented to the consumers via Internet.

The understanding of the technical aspect of recommendation systems builds the foundation of its importance in product promotion effectiveness. Currently, many of the popular websites such as Netflix, Amazon, Taobao, and Shopee have adopted recommendation systems. For instance, Netflix designed the algorithm and analysed user profile such as watching record, watching time, video's categories or the data from those customers who have similar taste to offer recommendations that might meet customer preference (Gomez-Uribe and Hunt 2015). Additionally, Amazon, the world's largest online retailer, also collected users' data through AI and adopted collaborative recommendation systems to provide suggestions in the light of matching users to similar customers. In fact, Nguyen et al. (2019) mentioned that 35% of Amazon's revenue came from its recommendation agent, and there is a 29% sales increase since it adopted the recommendation system. These facts support the claim of the importance of recommendation systems in product promotion.

Moreover, the evolution of the business landscape toward the digital economy and digital marketing are the strong facilitators for adopting internet-based promotional tools such as recommendation systems. However, this optimistic opportunity is countered by the phenomena of information explosion among the consumers. Consumers are increasingly finding it challenging to filter the avalanche of information being thrown at them. Simultaneously, firms are getting more competitive not just by promoting their goods and services digitally, but also by figuring out how to outperform their competitors in this web-based ecosystem. Typically, firms are interested in long-term survival and the success of their websites. In view of the opportunities and challenges, the recommendation system is a way forward and an effective promotion recommendation system is called for.

2.2 Trust and product promotion

While recommendation systems are essential in promoting goods and services, they are not the sole determinant of promotion effectiveness. In light of the current information explosion faced by the consumers, the core concern is attributed to trust. Consumers' willingness to adopt the recommendation is determined by their trust in recommendation systems, which can be developed through pleasant experiences. Numerous studies on trust have been done in the field of information system (IS), such as Adamopoulou and Symeonidis (2014), Gefen (2002), Grabner-Kräuter and Kaluscha (2003), Moody et al. (2014), highlighting trust as a key enabler in e-commerce. While Lim et al. (2020), Pu and Chen (2006; 2007) and Zanker's (2012) studies review the role of explanation in the development of trust mechanism, little has examined the effect of trust-based recommendation systems in product promotion effectiveness. To begin the examination of trust-based recommendation systems in product promotion effectiveness, the understanding of the product promotion is required.

In the marketing context, the term "sales promotion" refers to the overall armoury of marketing communications (Yeshin 2006), which is used to present the monetary and non-monetary benefits perceived by the consumers (Chandon et al. 2000). According to

Chandon et al. (2000), the effectiveness of the promotion lies in the hedonic benefits and utilitarian benefits. Hedonic benefits are in forms of monetary and nonmonetary promotions that provide consumers with opportunities such as entertainment, exploration, and value expression, while utilitarian benefits provide consumers with shopping convenience, higher product quality, and savings (Cham et al. 2018; Chandon et al. 2000). Drawing from the evidence from the past literature and the congruency framework by Chandon et al. (2000), the present study defines product promotion as offering consumers a product with an array of hedonic and utilitarian benefits through value expression, entertainment experience, exploration opportunity, superior product quality information, and improved shopping convenience. Due to the exponential growth of communication channels and advanced information technology, product promotion is flourishing profoundly in digital marketing. Adding on, Chen et al. (2013) pointed out that a lack of governance and explosive information phenomena have led to the emergence of such fraudulent cases online. In view of these two stands, the elements of trust come into the picture to bridge the gap between consumers and businesses. It is fundamentally crucial for both online shoppers and consumers as well as the internet ecosystem as a whole.

2.3 Trust-based recommendation system

The importance of trust has been acknowledged in many areas such as retailing (Cheah et al. 2020a, b, c), negotiation (Bazerman and Moore 1994), labour-management relations (Taylor 1989), leadership (Atwater 1988), communication (Giffin 1967), performance appraisal (Cummings 1983), management by objectives (Scott 1980), self-managed work teams (Lawler 1992), and game theory (Milgrom and Roberts 1992). Usually, trust indicates a positive expectation and confidence toward a particular subject (Lewicki et al. 1998). Subsequently, the study of trust has also expanded the field of information technology because of its rapid development. For instance, Gefen et al. (2008) presented the conceptual foundations of trust in online environments in order to improve the practice in the domain. Meanwhile, Kim (2012) studied the trust element in online shopping and informed that trust is interrelated with belief, intention, or attitude. His findings explained that initial impression for a product is influenced by consumers' initial trust which could influenced their purchase intention through attitude. In fact, trust plays a significant role in product promotion effectiveness as a result of today's highly dynamic and decentralized environment, where data is abundant and uncertain. Trust is construed as a key factor in the process of decision making. Gefen et al. (2008) also pointed out the target of trust toward an object (such as trust in the competence and integrity of a recommendation system which is a component of a website), leads to a behavioural belief (using the website would offer an efficient product search), which in turn has an impact on the website's adoption. Trust-based recommendation system exemplifies trust between users particularly consumers. Komiak and Benbasat (2008) elaborated that consumers will attribute the types of belief of the recommendation system through trust-building process. Henceforth, the trust of the recommendation system is recognized in terms of the system's benevolence, competence, and integrity (Cheah et al. 2020a, b, c; McKnight et al. 2004; Xiao and Benbasat 2007).

As for the current research, Mayer et al.'s (1995) Integrative Model of Organizational Trust is adopted to examine the recommendation system for product promotion effectiveness. Accordingly, trust is defined as the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party (Mayer et al. 1995). The underlying conditions that contribute to trust have been substantially considered in the literature with a different number of characteristics. For instance, Strickland (1958) identified a single trustee characteristic for trust, that is responsibility, whereas other scholars (e.g. Butler 1991) delineated as extensive as ten characteristics. Nevertheless, Mayer et al. (1995) reviewed a large volume of literatures by summarizing and categorising three characteristics of a trustee, namely competence trust, benevolence trust and integrity trust. Consistently, McKnight et al. (2002) expounded these trust beliefs in e-commerce that competence belief is a consumer's perception that a recommendation system has the ability, skills, and expertise to perform effectively in specific domains; while benevolence belief is a consumer's perception that a recommendation system cares about the consumer and therefore acts in the consumer's interest, and integrity belief is the perception that a recommendation system adheres to a set of principles (e.g. honesty and keeping words) that are generally accepted by consumers. The proceeding sections provide further discussion of the respective trust.

2.4 Competence trust

According to Brandt et al. (2005), competence can be explained as one's capability to perceive patterns effectively and able to provide valid reasons and response based on respective expertise. In other words, competence is regarded as the ability of an individual to interpret information correctly and it is often incorporated into certain skills along with the knowledge to use a certain system (Nooteboom 2002; Tyler 1996). Moreover, competence trust refers to the perceived trustee's expertise, skills, and abilities that improve his/her performance within a particular domain (McAllister 1995; Lane and Bachmann 1998), i.e., the recommendation system in the current context. The view of trustee's competence serve as a platform without the reliance on faith and competence trust produces sound decisions. Interestingly, Schiffrin and Schneider (1977) claimed that competence within a certain domain is also found to rely on automated processes, which are often parallel and function independently, similar to visual perception and pattern recognition.

In addition, Komiak and Benbasat (2004) put forth the nexus of consumers' rational expectation of the recommendation system in generating noble product suggestions. They further elaborated that competence trust is the procedure that user transforms the competence of recommendation system into trustworthiness-related characteristics, which was processed via item's ability assessment. This trustworthiness formed through competence trust produces positive effects in the inter-organizational systems. Ibrahim and Ribbers (2009) found that competence trust positively influences the use of human-knowledge resources, resources related to interlinkage of business processes, and organizational domain knowledge resources. As such, competence trust is part of the perceived recommendation system trust. Recommendation system advances on human-knowledge resources (i.e. trust from consumers), resources from interlinkage of business processes and organizational domain knowledge resources (i.e. the web-based recommendation system created by the organization in which inter-organisational to assist consumers to filter goods and services information before purchase) in the current research context.

2.5 Benevolence trust

As compared to competence trust, benevolence trust falls under the category of emotional-based trust. Benevolence trust indicates a belief in the benevolence of another party's actions in return, it can reduce concerns about opportunism and enhance mutuality (Wu et al. 2010; Tan et al. 2019). Given the uncertainty and potential risks of virtual interactions, Wu et al. (2010) emphasized the importance of benevolence trust in providing a mechanism needed for successful virtual member–community partnerships in the overwhelming online information ecosystem. Komiak and Benbasat (2008) informed that benevolence trust is the consumers' affective feeling of secure and comfortable when deciding with the help from the recommendation system. The presence of benevolence trust causes consumers to transform the benevolence recommendation system into trustworthiness-related characteristics and affect-based trust (Slonim et al. 2001), in which these are people trusting process that is based on target's internal motivations. Congruently, Ganesan and Hess (1997) concurred that interpersonal benevolence has a strong effect on consumers' commitment than other forms of trust. McKnight et al. (2002) also argued that, in situations whereby consumers choose to disclose their personal information to the service provider, they would be more concerned about its benevolence and integrity and less about its competence. In fact, Wu et al. (2014) asserted that benevolence trust has more significant effect on consumer continuance use of online social network platforms than any other factor. The discussions justified the inclusion of benevolence trust in perceived recommendation system trust.

2.6 Integrity trust

Integrity is a common concept that had been discussed as the antecedent to trust by a large number of theorists. Generally, the relationship between integrity and trust involves the trustor's perception that the trustee adheres to a set of principles that the trustor finds acceptable. Accordingly, McFall (1987) illustrated the rationale for the importance of both the adherence to and acceptability of the principles, which often follow some set of principles that defines personal integrity. Therefore, integrity trust is a type of cognitive trust. Gefen and Heart (2006) highlighted the role of integrity trust in e-commerce's international phenomenon and claimed that integrity trust affects the online consumer's intentions to engage in a purchase. Additionally, Komiak and Benbasat (2004) informed that integrity trust refers to consumer's rational expectation of the ability of a recommendation system to offer objective suggestions. They further explained that integrity trust is the procedure that user transforms the integrity of the recommendation system into trustworthiness-related characteristics and thereby relates to the concept of the intentional process (Doney and Cannon 1997) and affect-based trust (Slonim et al. 2001).

In the current context, integrity trust is a cognitive and affective-based trust in which the trustor's attributions concern of the target's competence, reliability, and dependability based on available knowledge about the target; and the motives for a target's behaviour. Integrity trust forms the trusting process of people based on the target's internal motivations. Coincide with the existing research objective, integrity trust is included to measure the perceived trust of the recommendation system. The inclusion is well-grounded in past approaches of trust such as McKnight et al. (2002) points the equal importance effect of integrity trust apart from benevolence trust when consumers disclose their personal information to the service provider; while Gefen and Heart's (2006) findings of integrity trust primarily affect intentions to engage in an e-commerce purchase. As such, integrity trust is being considered in the perceived recommendation system trust.

2.7 Product promotion effectiveness

Product promotion refers to the positive promotional method that are used to attract existing or potential customers to reinforce their motivation to purchase goods which would lead to the increase of financial performance of the company (Hultink et al. 1997). Product promotion effectiveness therefore is defined as the ability of recommendation systems to attract the users' attention and create interests for them (Hostler et al. 2011). The prevalence of e-commerce and digital age has given product promotion an equally easy and tough time. Product promotion gets easier when there are many platforms that facilitate e-commerce promotion with the development of digital age. However, the rise of e-commerce and digital age also means that merchants are getting more competitive in marketing and promoting their products and services through the internet. The intense competitiveness is arising from the increasing amount of information available which led to the phenomenon of information explosion.

Due to the growing availability of data, managing such high volume of information becomes more difficult. This issue is severely encountered by both consumers and merchants in the product promotion effort. On one hand, consumers are facing a tough time to filter the appropriate and correct information for their purchasing decision. While on the other hand, merchants are encountering a challenging moment to outdo its rivals by delivering interesting and correct product information on time to the consumers in hoping to close the sale. The former issue could be mitigated through recommendation systems which seek to filter and predict the consumers' preference by shortlisting a list of products for them. However, the latter issue persists as merchants need to be innovative to outperform their rivals. In this context, the current research attempts to examine the product promotion effectiveness through the trust-based recommendation system. Assuming that the consumers exhibit some level of trust in the recommendation system, most likely they will end up buying the product. Much prior research has examined the relationship between trust and product promotion. Positive results were derived by Hu et al. (2002) and Luk and Yip (2008) that established trust would improve the promotion effectiveness and further influence the final purchasing motivation and intention. Nevertheless, many changes have taken place since the last decade in the e-commerce arena such as the increase in digital buyers, the pervasiveness of social media and further advancement in technology (Cham et al. 2016; Cheah et al. 2019). Thereupon, this research is carried out to re-examine the trust-based recommendation system on product promotion effectiveness toward current generation of digital buyers.

3 Research framework and hypotheses development

By advancing the Theory of Social Responses and the discussion of past literature, it sets the scene to develop the following research framework to examine the perceived trust-based recommendation systems toward product promotion effectiveness. Figure 1 exhibits the research framework as a knowledge-based approach to enhance product promotion effectiveness by dealing with consumers' trusting beliefs of recommendation systems. In order to obtain more holistic findings, the target respondents are further examined through different gender groups. Additionally, weighted PLS-SEM (WPLS-SEM) algorithms is applied for the representativeness of the sample (Cheah et al. 2020a, b, c).

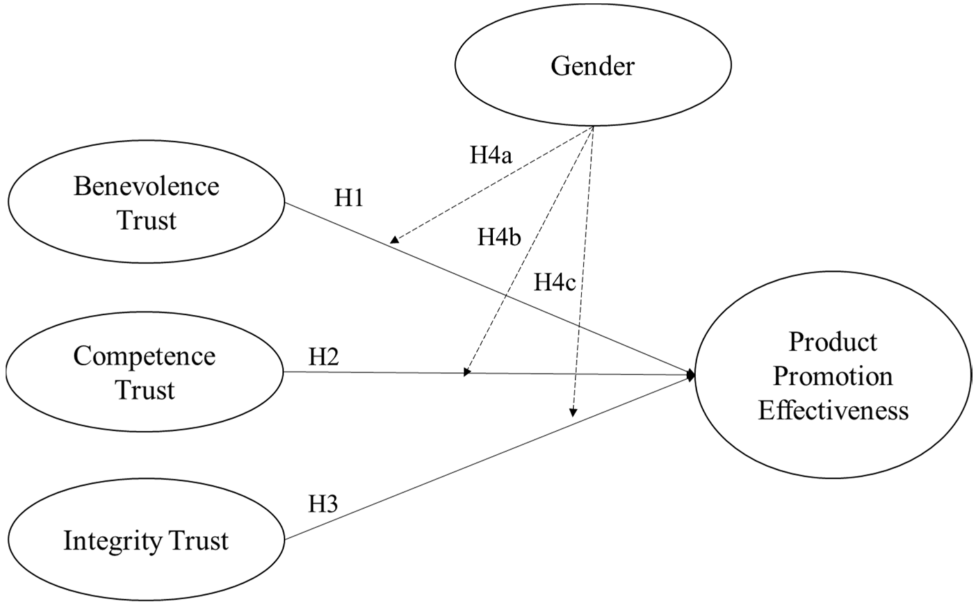

Fig. 1 Research framework

The theory of social response is also known as the Stimulus Organism Response (SOR) theory, which was developed by Mehrabian and Russell (1974). SOR theory informs that stimuli (S) leads to perception or feelings of an organism (O), which creates the response (R). Current study draws on the S–O–R concept in the recommendation system context by relating the recommendation system as the Stimulus with the online consumers being the representation of Organism and intention to purchase the product or service recommended as the Response (Perumal et al. 2021). Accordingly, consumers treat computerised agents as social actors, and thereby form social relationships that involve trust. In the current research context, the recommendation systems are considered as the computerised agent while the trust relationship is formed when the consumers buying into the recommendation generated by the system.

Drawing from the understanding of trust by Xiao and Benbasat (2007) and McKnight et al. (2002), the current study delineates trust in a recommendation system as an individual's beliefs towards the recommendation system's benevolence, competence, and integrity. When these three types of multi-dimensional trusts are established, it constitutes to the perceived recommendation systems' trust. Competence and integrity trust are further categorised as cognitive trust while benevolence trust falls under the category of emotional trust. The propensity of trust by each individual consumer magnifies or reduces product promotion effectiveness. The current study also further investigates the perceived trust of recommendation systems between male and female consumers for more insightful findings. To address the representativeness, the proportion of Internet users according to age and gender were derived from the Malaysian Communication and Multimedia Commission (MCMC) survey in 2018.

Accordingly, benevolence trust represents the emotional aspect, which indicates the affective feelings of the consumer that is secure and comfortable when making a decision with the help of the recommendation system (Komiak and Benbasat 2008). This is consistent with Doney and Cannon's (1997) explanation that benevolence trust is the procedure that user transforms the benevolence of recommendation systems into the trustworthiness associated characteristics of intentionality process. The presence of benevolence trust creates comfy feelings of the consumers to adopt the recommendation posted by the recommendation systems and thereby results in effective product promotion. With this in mind, Hypothesis 1 is formulated:

Hypothesis 1 There is a significant positive relationship between benevolence trust and product promotion effectiveness.

Competence trust denotes the consumer's belief that the ability, skills, and expertise of the recommendation system to perform effectively in the context of generating sound recommendations. In other words, the competence-based trust exists when consumer believes that the recommendation system has the knowledge and expertise in relation to a specific domain (Jarvenpaa et al. 1998) and thereby constitute the perceived recommendation system trust. As such, the presence of competence trust will thereby lead to effective product promotion. Henceforth, the following hypothesis is then developed:

Hypothesis 2 There is a significant positive relationship between competence trust and product promotion effectiveness.

Integrity trust is often considered as an individual level virtue (Palanski et al. 2011). In the context of e-commerce, integrity trust relates to content truthfulness which guides customers in their online purchase decisions. Trust is also a positive expectation about the future action of partnership. When the content on the merchants' web is truthful and the promise of delivering the product as indicated is carried out, the integrity trust relationship is established. This indicates the importance of integrity as a source of trust (Vance et al. 2009). Intuitively, if all product information on the web is precise and truthful, consumers will easily find the products and lead to potential positive expectations. Therefore, the following is hypothesized:

Hypothesis 3 There is a significant positive relationship between integrity trust and product promotion effectiveness.

Gender is an evergreen subject matter in many research topics and field of studies, such as marketing, psychology and behavioural studies (Lim and Cham 2015; Lim et al. 2019, 2021; Meyers-Levy and Maheswaran 1991; Putrevu 2004; Richard et al. 2010). The recent development of internet age has further enriched the discussion of much research through the gender perspective. According to the Internet World Stats (2019), overall male internet users are more than female internet users. For instance, 84.9% of males and 80.3% of females use the internet in Europe. Meanwhile, a similar pattern is observed in Asia Pacific for the year 2019, with 54.6% of male internet users and 41.3% of female internet users. Thus, it is essential for advertisers to understand as much as possible about gender differences in order to employ effective advertising design features. Acknowledging the importance of gender perspective, Tsichla et al. (2016) insisted "a thorough understanding of gender-specific evaluations and desires pertaining to web design is paramount". Accordingly, advertisers shall understand the different responses from males and females on online advertising stimuli. Subsequently, research (such as Kempf et al. 1997; Shavitt 1998; Wolin and Korgaonkar 2003) pointed out that males tend to have more positive attitudes toward advertising than females (Kempf et al. 1997; Shavitt 1998; Wolin and Korgaonkar 2003).

Additionally, Rodgers and Sheldon (1999) informed that male users show more favourable attitudes toward online shopping than female users. Subsequently, Davis et al. (2014) in their research examining the gender perspective between hedonic shopping motivation and purchase intentions uncovered that male shoppers have higher online purchase intentions than females. Besides of intention, Mahzari and Ahmadzadeh (2013) found that females have different preferences from males regarding web site design features such as shapes, colours, and images. These differences moderate the relationships between website stimuli and shopping outcomes, i.e., online purchase intentions. Cyr and Bonanni (2005) also highlighted the gender differences in the virtual communities based on the sociolinguistic theory. All these discussions justified the inclusion of gender into the current study to explore the trust-based recommendation systems in product promotion effectiveness. Based on this preliminary evidence and discussion, the following hypotheses are developed:

Hypotheses 4a There is a difference between male and female consumers in terms of the relationship between benevolence trust and product promotion effectiveness.

Hypothesis 4b There is a difference between male and female consumers in terms of the relationship between competence trust and product promotion effectiveness.

Hypothesis 4c There is a difference between male and female consumers in terms of the relationship between integrity trust and product promotion effectiveness.

4 Research methodology

Quantitative method is utilised to carry out the current study. It is a cross-sectional survey guided by the post-positivism assumptions (Creswell 2012). Partial least squares structural equation modelling (PLS-SEM) is employed to perform the statistical analysis of the developed research model and to test the six hypotheses formulated. The rationale for the adoption of PLS-SEM is owing to its nature of regression-based technique in marketing fields and its ability to estimate relationships in path models with latent and manifest variables (Lohmöller 1989; Wold 1985). Additionally, PLS-SEM is a causal-predictive method (Chin et al. 2020; Hwang et al. 2020; Jöreskog 1982) that enables maximization of the amount of explained variance of the endogenous constructs embedded in a path model grounded in well-developed causal explanations (Sarstedt et al. 2017). Therefore, PLS-SEM results are suitable to generate out-of-sample predictions, in which it refers to the interplay between explanation and prediction theory (Gregor 2006). Moreover, PLS-SEM is construed as the variance-based structural equation modeling which all the components of the constructs are selected based on how much variance they explain in the predicting variables and between the predicting and the responding variables. Rigdon et al. (2017) explain that PLS-SEM applies a series of regressions to maximize the explained variance of the endogenous construct. In fact, PLS outperforms OLS by its's ability to fit multiple response variables in a single model which meets current research setting.

According to Lohmöller and Wold (1989), in a situation where there is an abundance of data and low theoretical support, PLS-SEM is the appropriate analytical tool because it allows the researcher to examine the data and assess many different configurations. Current research context is characterised as "data-rich" owing to the nature of E-commerce which enable the capture of big data. Additionally, the volume, variety and velocity of the data in E-commerce mimic the challenge of big data that is complex and often lack of comprehensive theory of substantiation (Stieglitz et al. 2014). Henceforth, it justified the use of PLS-SEM for statistical analysis. Additionally, a more robust weighted PLS-SEM (WPLS-SEM) algorithm recommended by Cheah et al. (2020a, b, c) was adopted to perform the analysis. Cheah and colleagues asserted that WPLS-SEM enables sample representativeness in PLS-SEM analysis and also to address the issues arise from non-probability sampling methods such as lack of representativeness and generalisability (Levy and Lemeshow 2013), uneven selection probabilities, non-response and non-coverage (Kalton and Flores-Cervantes 2003). The use of WPLS-SEM allows researchers to assign sampling weight to each observation and permit the weighted observation to represent the population of interest. These features of PLS-SEM and WPLS-SEM meet the current research objectives to explore the causal relationship between the trust-based recommendation systems and product promotion effectiveness with better representativeness; as well as its predictive relevance of developed research framework with a gender perspective in mind. This is the core contribution of current research in which Cheah et al. (2020a, b, c) highlighted that many existing researches had demonstrated its' comprehensive in term of statistical reliability and validity for the generalisability of their findings but omitted the fundamental issue of representativeness. Therefore, the current study aims to bridge the methodological gap in order to generate new insights on the context of recommendation systems.

Before the questionnaire was distributed, pretesting was conducted with the aim to minimize potential bias (Podsakof et al. 2012; Spekle and Widener 2018), to prevent potential measurement errors and to ensure that the questionnaire was structured in an easy-to-understand manner by the target respondents (Fowler 2013). Feedback gathered from the pretesting was incorporated. Among others are some phrases that were corrected for the purpose of clarity. The revised version of the questionnaire was distributed using non-probability sampling technique. Probability sampling technique is not suitable for current research as there is no sampling frame available in the context of online shopping. Owing to the nature of this study, non-probability, snowball sampling technique was used. This technique allows the researchers to collect data from respondents who had ever used recommendation systems when they were shopping online. Adopting the purposive technique enable researchers to share the questionnaire to identified specific respondents who had previously shopped online with recommendation systems experience. It was administered by the researchers, sending the questionnaire via Google document link and/or hardcopy of the questionnaire to the referred respondents.

To determine the sample size required, Memon et al.'s (2020) suggestion was adopted through the use of *G**Power 3.1.9.7 programme. Following Hair et al.'s (2017) guide as the most common recommended setting for social and business science research, a medium effect size of 0.15, α at 0.05, and power at 0.80 was used as the input parameters. Based on Fig. 1, there are three predictors in our research model, therefore "3" was entered as input parameter. *G**Power estimates that the minimum sample size required for the research model is 119. In order to ensure sufficient complete responses are collected, 500 questionnaires were distributed via Google document link and hardcopy questionnaires. The researchers also assured the respondents of the anonymity of their responses and did not disclose their names to any merchants. Data collected was strictly meant for research and academic purpose. T-test was performed to check for any significance difference between two data collection approaches. A value below zero was obtained, indicating that there is no significance difference between the responses collected from Google document link and hardcopy questionnaires. At the end of data collection process, a total of 315 responses were received. However, only 310 responses were completed, thus yielding a 62.0% response rate. The demographics of the 310 responses are exhibited in Table 1. All the constructs were measured using well-established scales adapted from existing literature on a five-point Likert scale, ranging from (1) "strongly disagree" to (5) "strongly agree". Measures for competence trust (5 items), benevolent trust (3 items) and integrity trust (3 items) were drawn from Benbasat and Wong (2005) while product promotion effectiveness was borrowed from Hostler et al. (2011).

4.1 Common method bias

Common method bias (CMB) is a potentially serious methodological issue in marketing research. CMB happens when all variables (independent variables, dependent variables, mediating and moderating variables) are collected using the same method in survey research (Podsakoff and Organ 1986). In other words, CMB occurs when the estimates of the relationships between two or more constructs are biased because they are measured with the same method. As such, the data is often susceptible to possible artificial inflation of relationships. Commonly, marketing research uses cross-section survey whereby a single administration is carried out in self-reported forms. Hence, the issue of CMB occurs and could hamper the reliability and validity of the measures. With

Table 1 Respondents' profile

	Frequency	Percentage (%)
Gender		
Male	165	53.2
Female	145	46.8
Age group		
< 20	9	2.9
20 s	153	49.4
30 s	57	18.4
40 s	46	14.8
50 s	25	8.1
60 s and > 60 s	20	6.5
Education level		
High school	10	3.2
College	181	58.4
Undergraduate	116	37.4
Post graduates	3	1.0
Frequency of online purchase		
Everyday	22	7.1
1–2 days	224	72.3
3–4 days	37	11.9
5–6 days	27	8.7

these concern in mind, the researchers have addressed the issues of CMB in this study through procedural strategies proposed by Jordan and Troth (2019) and the statistical approach recommended by Kock (2017).

In term of the procedural approach, Jordan and Troth's (2020) suggestions were considered. Jordan and Troth (2020) explained the cause of CMB is arouse from a single administration survey in which independent variables and dependent variables are collected simultaneously with a similar format such as the use of Likert-type scale. The researchers have pre-anticipated the issues of CMB and decided on the more preventive procedural strategies prior to data collection. Drawing from the recommendation by Hair et al. (2015) and Podsakoff et al. (2012), the researchers have included a research information coversheet in order to increase the probability of response accuracy. Besides that, the researchers have also adopted Jordan and Troth's (2019) suggestions to minimise the scale properties shared by measures of the predictor and criterion variables for CMB reduction purpose. For instance, the questionnaire survey was developed by including 7-point and 5-point Likert-type scales. Apart from these preventive measures, the researchers understand the importance of clarity and unambiguous terms and questions. A pre-test with 20 consumers who had experienced with recommendation system was conducted to rule out ambiguity in the instructions and wording of the questionnaire. No major issues arise and minor amendment in wordings was done. Questions in the finalised survey are concise and simple without double-meaning items before extending to the targeted respondents.

For the statistical approach, full collinearity VIFs (AFVIF) was used to assess CMB to examine the correlations between items of two constructs. The analysis results obtained an AFVIF value of 1.726 < 3.3, which indicates that CMB does not interfere with our measurement results. Therefore, Common Method Bias is not an issue in current results findings based on both preventive procedural strategies, explained before the data collection and statistical approach.

5 Results and findings

5.1 Respondents' demographic profile

A total of 310 complete responses were collected with 53.2% male consumers and 46.8% female consumers. Majority of the consumers participated in this research are in their 20 s (49.4%) and having a tertiary education (96.8%). Moreover, it was found that most of the respondents purchased online as frequent as 1 to 2 days (72.3%).

5.2 Determination of sampling weights

In order to address the concern of representativeness, this research study adopted the weighted PLS-SEM (WPLS-SEM) algorithm before performing the analysis. The determination of the sampling weight was calculated based on the population of Internet users' demographics. Malaysian Communications of Multimedia Commission (MCMC) had conducted an Internet Users Survey in 2018. According to the survey, there are 2.87 million internet users with 53.2% of men and 46.8% of female. Based on this information Table 3 was established to calculate post-stratification weights of Internet users from Table 2 Age* Gender cross tabulation.

Following the guidelines by Cheah et al. (2020a, b, c), analysis within-cell sample is required to warrant adequate sample elements in all cells. With reference to Table 2, the first cell in the sample (the cell of below 20 years old of male and female) is too small (five males and four females). Similarly, the last cell in the Education level, post graduates is too small. i.e., 3 respondents. Small observations could pose a threat in weight computation. In this regard, the present analysis has excluded the cell of below 20 years old of male and female. Henceforth, the total sample size in this study was 301 (310 − 9 = 301).

In determining the sampling weights, the proportion of the population and the proportion of the sample were calculated to establish the weight by diving the proportion of the population with proportion of the sample. Table 3 exhibits the post-stratification weight of the internet users based on the MCMC Internet users survey 2018 in current research study. The weight (PP/PS) was then inserted to each observation for the standard PLS-SEM assessment.

5.3 Measurement model assessment

After the establishment of post-stratification weight, the standard evaluation of PLS followed. It begins with the measurement model assessment before proceeding to structural model assessment. Current research model only consists of reflective measure, i.e., Mode A measurement in PLS-SEM. Reflective measures indicate the effects or manifestations of an underlying construct. Adding on, the individual items of reflective measures could be interchangeable, and any single item can be left out without altering the meaning of the construct, so long the construct has sufficient reliability (Hair et al.

Table 2 Age gender cross tabulation

	Gender		Total
	Male	Female	
Age			
< 20			
Number	5	4	9
% within age	55.555	44.444	100.00
% within gender	3.033	2.759	5.792
20 s			
Number	60	93	153
% within age	39.216	60.780	100.00
% within gender	36.360	64.140	100.500
30 s			
Number	38	19	57
% within age	66.667	33.333	100.000
% within gender	23.030	13.103	36.134
40 s			
Number	33	13	46
% within age	71.739	28.261	100.00
% within gender	20.000	8.966	28.97
50 s			
Number	16	9	25
% within age	64.000	36.000	100.00
% within gender	9.697	6.207	15.90
60 s & > 60 s			
Number	13	7	20
% within age	65.000	35.000	100.00
% within gender	7.879	4.828	12.706
Total			
Number	165	145	310

Table 3 Post-stratification weight of internet users

Age and gender	Population (N)	Proportion of population (PP)	Sample (n)	Proportion of sample (PS)	Weight (PP/PS)
20 s: Male	5,079,900	0.177	60	0.199	0.888
20 s: Female	3,530,100	0.123	93	0.309	0.398
30 s: Male	4,385,647	0.153	38	0.126	1.210
30 s: Female	3,047,653	0.106	19	0.063	1.682
40 s: Male	3,031,007	0.106	33	0.110	0.963
40 s: Female	2,106,293	0.073	13	0.043	1.699
50 s: Male	1,964,228	0.068	16	0.053	1.288
50 s: Female	1,364,972	0.048	9	0.043	1.101
60 s and above: Male	1,100,645	0.038	13	0.043	0.888
60 s and above: Female	764,855	0.027	7	0.023	1.146

2017). An evaluation of the reflective measures entailed the examination of internal consistency through composite reliability (CR) and Cronbach's alpha, convergent validity through indicator loading and average variance extracted (AVE); and discriminant validity through heterotrait-monotrait ratio of correlations (HTMT).

Recently, Cronbach's alpha is considered conservative estimate reliability while CR is a more liberal measure. Hence, CR is considered and the CR values of all constructs were greater than the benchmark value of 0.70 providing evidence that constructs reliability was demonstrated. Additionally, rho_A, the newly recommended measure by Dijkstra and Henseler (2015) was estimated and the reliability estimates fall within the threshold of 0.70, (i.e., ranging from 0.728 to 0.899) as proposed by Henseler et al. (2019). Item BT1 was removed due to the loading obtained was below the recommended threshold of 0.708 (Hair et al. 2017). Convergent validity was also established among the 18 items, 16 had indicator loadings exceeding the ideal level of higher than 0.70 (Hair et al. 2017) and all the constructs with their average variance extracted (AVE) values above the recommended threshold of 0.50. The measurement model assessment result is shown in Table 4 and Fig. 2.

The discriminant validity was assessed through HTMT procedure prescribed by Henseler et al. (2015). As illustrated in Table 5, all values of HTMT were lower than the conservative threshold of 0.85 (Henseler et al. 2015) with confidence intervals included the value of 0.9, thus evidence the achievement discriminant validity. Overall, the results depicted in Tables 4 and 5 confirmed the fulfilment of measurement model validity and reliability.

Table 4 Measurement model assessment results for WPLS-SEM

Construct	Items	Outer loading	α	rho_A	CR	AVE
Benevolence trust	BT1*					
	BT2	0.895	0.725	0.728	0.879	0.784
	BT3	0.876				
Competence trust	CT1	0.784	0.826	0.832	0.878	0.59
	CT2	0.834				
	CT3	0.814				
	CT4	0.763				
	CT5	0.884				
Integrity trust	IT1	0.875	0.87	0.876	0.92	0.794
	IT2	0.913				
	IT3	0.822				
Product promotion effectiveness	PE1	0.725	0.889	0.899	0.915	0.643
	PE2	0.772				
	PE3	0.827				
	PE4	0.868				
	PE5	0.792				
	PE6	0.725				

*Item deleted

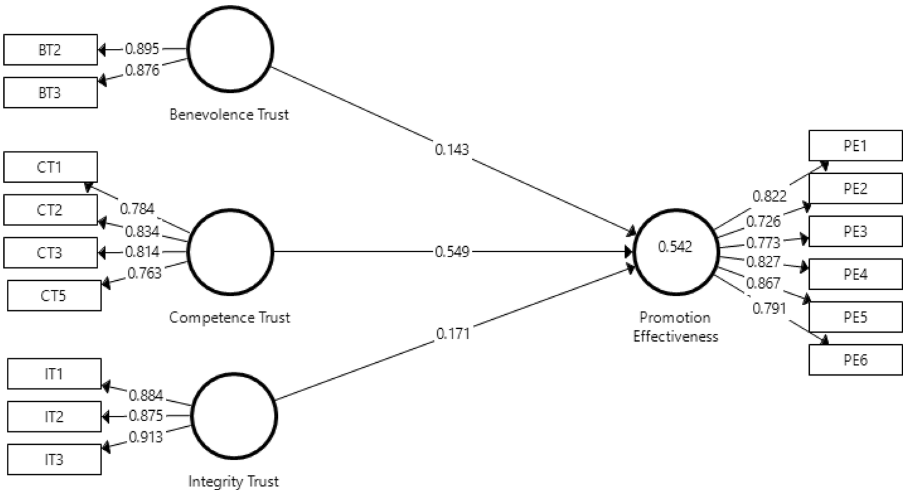

Fig. 2 WPLS-SEM with path coefficient, coefficient of determinant, and loading

Table 5 Discriminant validity (HTMT criterion)

	1	2	3	4
1. Benevolence trust				
2. Competence trust	0.591 [0.469; 0.722]			
3. Integrity trust	0.453 [0.315; 0.561]	0.637 [0.545; 0.730]		
4. PPE	0.569 [0.427; 0.693]	0.817 [0.730; 0.897]	0.575 [0.479; 0.670]	

PPE Product promotion effectiveness

5.4 Structural model assessment

According to Hair et al. (2019), structural model assessment entails the collinearity evaluation among the exogenous constructs, testing the significance and relevance of path coefficients, β as well as indirect effects and total effects (if applicable), examining the model's predictive accuracy through co-efficient of determination, R^2 followed by assessing the model's out-of-sample predictive power, and model comparison, if necessary. The collinearity evaluation among constructs was performed by examining the VIF values of the exogenous constructs. VIF values of less than 3 are considered as ideal values (Hair et al. 2019). The examination of VIF values showed that all the values were ideally less than 2, indicating no cause for concern with respect to collinearity issues as displayed in Table 7.

Subsequently, one-tailed bootstrapping test using 1000 resampling was conducted at 5% significance level based on the direction of the hypotheses. The bootstrapping test was meant to generate the t-values to measure the statistical significance of the path coefficients, β hypothesised. Table 6 illustrates the results of path co-efficient assessment for the hypothesized direct relationships. All the three direct relationships are found to be significant (H1: Benevolence Trust → Promotion Effectiveness, $\beta = 0.220$, $p < 0.05$; H2: Competence Trust → Promotion Effectiveness, $\beta = 0.487$, $p < 0.05$; and H3: Integrity Trust →

Table 6 Hypotheses testing results for full data

Hypothesis	β	SE	t-statistics	p-values	Decision
H1: Benevolence trust → PPE	0.220	0.069	3.190	0.001	Supported
H2: Competence trust → PPE	0.487	0.083	5.888	0.000	Supported
H3: Integrity trust → PPE	0.139	0.055	2.505	0.006	Supported

PPE product promotion effectiveness; *SE* Standard error

Table 7 Structural assessment results

Construct	R^2	Adjusted R^2	f^2	Q^2	VIF	SRMR	AFVIF
Benevolence trust			0.056		1.916		
Competence trust			0.275		1.926		
Integrity trust			0.028		1.536		
PPE	0.552	0.547		0.341		0.090	1.726

PPE Product promotion effectiveness

Promotion Effectiveness, $\beta = 0.139$, $p < 0.05$). The structural assessment results are exhibited in Table 7. The higher the R^2 value, the greater the model's explanatory power is (Hair et al. 2019). Table 7 presents the R^2 and adjusted R^2 generated are good as there are above 0.5. Additionally, the effect size value generated by each construct in the model ranges from 0.047 to 0.320 indicating the present of small to large effect size. The predictive relevance value, Q^2 informed of the excellent endogenous variable (more than 0), which indicates that that the research model possesses predictive relevance. Moreover, the value of standardized root-mean-squared residual (SRMR) for this study is equal to 0.075, which indicates that the research model developed is fit to the data (Latan and Noonan 2017).

5.5 Predictive model assessment

More recently, Shmueli et al. (2019) highlighted PLS-SEM is a "causal-predictive" application and its' cruciality to assess path model's predictability power. For this reason, PLSpredict which based on the concepts of separating holdout and training samples with the objective to estimate the model parameters and evaluate model's predictive power was used. Mean absolute error (MAE) and Root mean squared error (RMSE) were used in the present study due to the symmetrical nature of the prediction error of the existing data (Chin et al. 2020). The results of predictive model assessment are presented in Table 8. The assessment results obtained inform of PLS-SEM < LM for the equal number of the indicators, hence, it concludes that the model has a medium predictive power.

5.6 Multigroup analysis

PLS-based Multi-group analysis (MGA) was used to compare the two groups of data collected according to gender. Henseler et al. (2016) and Hair et al. (2018) recommended the use of the Measurement Invariance of Composite Models (MICOM) prior to MGA. This process is vital

Table 8 Predictive relevance assessment

Indicators	PLS-SEM			LM			PLS-SEM-LM		
	RMSE	MAE	Q^2 predict	RMSE	MAE	Q^2 predict	RMSE	MAE	Q^2 predict
PPE1	0.608	0.469	0.370	0.613	0.474	0.359	−0.005	−0.005	0.011
PPE2	0.760	0.623	0.438	0.752	0.593	0.449	0.008	0.03	−0.011
PPE3	0.702	0.559	0.303	0.704	0.562	0.298	−0.002	−0.003	0.005
PPE4	0.695	0.524	0.242	0.683	0.506	0.268	0.012	0.018	−0.026
PPE5	0.610	0.432	0.161	0.591	0.417	0.211	0.019	0.015	−0.050
PPE6	0.696	0.563	0.336	0.703	0.56	0.323	−0.007	0.003	0.013

PPE Product promotion effectiveness

because invariance tests are aimed to determine whether, under different conditions of observation, the measurement models would produce the measures of the similar attribute (Henseler et al. 2016). MICOM approach comprises of three-step, such as (1) configural invariance; (2) compositional invariance; and (3) scalar invariance (equality of composite means and variances). MICOM process was executed to compare the male and female consumers in order to establish the linkages within the model to test H4.

Firstly, configural invariance was attained between the male and female consumers when the measurement models have the same basic factor structure in both groups. Compositional invariance was then assessed by using a permutation test. The results reveal that none of the c values are significantly different from one another in the permutation test. This is observed when all permutation c value results (=1) straddle the upper and lower boundaries of the 95% confidence interval, indicating that compositional invariance is established in the research model. The permutation p-values greater than 0.05 in Table 9 provide additional support for the constructs passing the measurement invariance test (Matthew 2017). Lastly, equality of composites' mean values and variances was assessed across the groups. The difference in the composite's mean value and variance ratio results must fall within a 95% confidence interval. Referring to Table 9, the results show that all composite constructs have non-significant differences in terms of the composite mean value and variances ratio as the results fall between the upper and lower boundaries of 95%. Full measurement invariance is thus established for male and female consumers.

Upon achieving full measurement invariance as displayed in Table 9, Matthew (2017) recommended to run PLS Algorithm and bootstrapping test for each group separately. The bootstrapping test results for the respective gender is exhibited in Table 10. The results inform that all the three hypotheses (H4a, H4b, and H4c) are supported with p values less than 0.10 indicating significant differences between the two groups (Matthew 2017). For both the male and female consumers, competence trust recorded the highest standard beta toward product promotion effectiveness with $\beta = 0.607$ ($p < 0.10$) and $\beta = 0.392$ ($p < 0.10$) respectively. For benevolence trust, the standard beta for male consumer is higher than the female consumers with $\beta = 0.190$ ($p < 0.10$) and $\beta = 0.149$ ($p < 0.10$). Lastly, female consumers have a higher standard beta for integrity trust as compared to their counterparts, which was recorded at $\beta = 0.253$ ($p < 0.10$) and $\beta = 0.125$ ($p < 0.10$).

Table 9 Measurement invariance assessment

Constructs	Configural Invariance (same algorithms for both groups)	Compositional invariance (Correlation = 1)		Partial measurement invariance established	Equal mean assessment				Equal variance assessment				Full measurement invariance established
		C = 1	CI		Diff	CI	*p* value	Equal	Diff	CI	*p* value	Equal	
Benevolent trust	Yes	0.996	[0.992, 1.000]	Yes	−0.176	[−0.258, 0.257]	0.174	Yes	0.281	[−0.452, 0.427]	0.206	Yes	Yes
Competence trust	Yes	0.998	[0.999, 1.000]	Yes	−0.098	[−0.269, 0.255]	0.454	Yes	−0.137	[−0.406, 0.425]	0.485	Yes	Yes
Integrity trust	Yes	0.997	[0.999, 1.000]	Yes	−0.033	[−0.254, 0.254]	0.786	Yes	0.272	[−0.294, 0.310]	0.073	Yes	Yes
PPE	Yes	0.999	[0.999, 1.000]	Yes	−0.214	[−0.258, 0.255]	0.102	Yes	0.150	[−0.361, 0.372]	0.437	Yes	Yes

PPE product promotion effectiveness

Table 10 Hypotheses testing results based on gender

Path relationship	Males				Females			
	Std. Beta	Std. Error	t-value	*p*-value	Std. Beta	Std. Error	t-value	*p*-value
H4a: benevolence trust → PPE	0.190	0.070	2.715	0.003	0.149	0.076	1.960	0.025
H4b: competence trust → PPE	0.607	0.072	8.401	0.000	0.392	0.096	4.100	0.000
H4c: integrity trust → PPE	0.125	0.069	1.808	0.036	0.253	0.081	3.112	0.001

PPE product promotion effectiveness

6 Discussions

This research adopted theory of social responses to scrutinise the impact of trust-based recommendation system in product promotion effectiveness. Specifically, cognitive and emotional trust was operationalised based on three constructs, namely competence trust, integrity trust, and benevolence trust to examine its' impact on product promotion effectiveness. Procedural approach was used in order to mitigate potential CMB before distributing the questionnaire on a large scale. Additionally, statistical approach was also performed by using full collinearity assessment (Kock 2015) and it revealed that CMB is not a concern in this research.

The results informed that trusted-based recommendation is the marvel of product promotion effectiveness with the three formulated hypotheses showing the statistical significance and therefore are supported. The results obtained are consistent with Xiao and Benbasat (2007) and McKnight et al. (2002)'s finding. Adding on, the R^2 value of 52.9% indicated that more than 50% of the variances in product promotion effectiveness is explained by the three trust constructs. These findings suggest that the presence of competence, benevolence, and integrity trust would lead to effective product promotion in online shopping.

Among the three constructs, competence trust showed a large effect size (f^2) of 0.320 signifying its' major contribution to product promotion effectiveness. Competence trust is highlighted in the capability process (Doney and Cannon 1997) and the attribution process (Chopra and Wallace 2003) which users transform the competence of recommendation system into trustworthiness-related characteristics. Furthermore, trustworthiness produces positive effects in the interorganizational systems through the usage of human-knowledge capitals to connect to the business processes (Ibrahim and Ribbers 2009). This logical illustration explains the rationale of competence trust displayed a large effect size as compared to benevolence and integrity trust.

Additionally, the effect of gender on the proposed framework was addressed through PLS-based multi-group analysis (MGA). The permutation test indicated that there is a significant difference between male and female consumers on their respective types of trust in product promotion effectiveness. Despite that, both groups show statistical significance toward competence trust on product promotion effectiveness, yet male consumers displayed higher path coefficient ($\beta = 0.607$) compared to their counterparts ($\beta = 0.392$). The disparity obtained between these two groups owes to the nature of competence trust that relates to the trustee's abilities, skills and expertise that facilitate performance within a specific domain (Mayer et al. 1995; McAllister 1995; Lane and Bachmann 1998), such as the recommendation system in the current context. Males are often considered as independent, confident and purposeful (Zhang et al. 2015), while females are characterized as friendly, generous, and sentimental (Eagly and Wood 1991). On the same note, males are frequently motivated by rational and achievable needs but females tend to be emotional and relational for expressive needs (Hoffman 1972). As such, it also explains on the overall scale, male consumers display a higher level of trust as compared to female consumers.

Further interpretation of the current findings denotes that despite the rapid changes in digital technologies, trust-based recommendation system remains to serve as an important element in the product promotion effectiveness. As such, congruent results were found similar to the findings from Xiao and Benbasat (2007) and McKnight et al. (2002).

7 Implications and contributions

Digital economy has fostered the revolutionary of digital marketing. The existing new digital technologies such as big data, virtual reality, and augmented reality have compelled marketing managers to be aware with the latest technological advancement and to be innovative and creative in marketing their products and services via the internet platform on a large global scale. The emergence of digital marketing ecosystem through the adoption of chatbots, virtual reality, artificial intelligence, and augmented reality have presented new opportunities and challenges for many businesses (Kannan 2017; Kumar et al. 2021).

As for the context of practical implications, the findings from the present study provide interesting insights for the organization's top management and their marketing team. Despite the development in digital marketing, current research findings enlightened that consumer's perceived trust in the recommendation system continues to play a vital role in determining the effectiveness of product promotion. Hence, there is no doubt that the top management of the business organizations, along with their marketing team needs to understand the importance of the system and consumer trust in their marketing strategy development. Creed et al. (2009) shared the similar opinion that in the internet-mediated platform, trust, privacy, and security are the core relational issues required constant update and improvement to embrace new changes. The operator of the recommendation system needs to go the extra mile in knowing how to build trust with their customers in today's competitive business environment. Instilling confidence within customers would be a significant guaranteed route to improve company performance, particularly in terms of numbers of engagement and establishing a loyal customer base. This is important as those users who trust the platform would continuously use the platform as a source of information for the purchasing activities. Moreover, trust among users would also enhance the platform reputation, users' level of satisfaction, loyalty, and willingness to recommend it to their family and friends. It was also argued that companies that fail to sustain trust in their customers would definitely limit their potential and competitive edge in competing in the marketplace.

In view of the importance of consumer trust towards the recommendation system, the platform operators need to be honest and transparent in their offering, ads, and pricing. It is recommended that the operators publish such information at the domain that is easily accessible by the customers. Such information is important to help consumers in making an informed decision and improve their level of confidence in deciding on the deals. Besides being transparent, the operators should also engage in reviews and testimonials of the consumers based on their consumption experience of specific products in the recommendation system. It is believed that such consumer-generated content sharing would enhance the confidence of consumers towards a particular product due to its inclusiveness and minimal effect of profit motivation. Moreover, the consumer-generated content is also perceived to be more trustworthy and reliable compared to those content created by the businesses. All these reviews and testimonials can be shared via recommendation system's website and social media platforms. For instance, the operators can share this information through various social media platforms such as Facebook due to its popularity among consumers.

Furthermore, businesses can enhance their credibility and reputation by ensuring their customer service is at the commendable level in order to enhance trust among their customers. By doing so, the entity will get a recommendation by the existing customers in which will enhance their image in the eyes of customers. Hence, the marketing team should focus and be committed to help their consumers in handling their issues on an individual basis. This "personal touch" could make the customers perceive the company favourably and enhance their likelihood to come back and recommend the company to their friends and family. Similarly, the outcome from the customer service is also expected to enhance the trust of first-time customers towards the company ads and their offering. As such, businesses need to provide relevant training to the staff who are involved with the customer service directly. Moreover, companies should also consider developing reliable standard operating procedures (SOPs) to facilitate all the processes that are related to customer service. This initiative is expected to reduce any uncertainties among staff in handling the customers and most importantly, to instil confidence in them. Moreover, businesses can also consider adopting appropriate rewards strategies to encourage their staff to perform at their optimal level.

The findings of this research are important and should be regarded as a useful guide for businesses and recommendation system operators to develop their marketing strategies. The results of this study suggested the importance of benevolence trust, competence trust, and integrity trust in influencing promotion effectiveness. Thus, this fact revealed that consumers' trust is a critical element in shaping their perception towards companies' ads and promotion as well as their product/service consumption. Although the importance of customer trust is not a new idea in marketing research, however, what this study proposed is the importance of customer trust towards online recommendation system and its relationship with the product promotion effectiveness. The findings from this study are expected to serve as a guide for the marketers and the industry players. Continuous improvement in recommendation systems incorporating new digital technologies along with a secured trust-based element is way forward.

This study contributes by extending the trust elements in the context of recommendation system which in the past, most of the past studies utilised trust elements in the e-commerce setting without considering recommendation system. Additionally, the findings also investigate the gender factor whereby male and female online consumers demonstrated incongruent trust level for different category of trust. In order to provide a reliable and comprehensive finding, the sampling weight adjustment was incorporated in our research methodology for a representative finding.

8 Limitations and recommendations

Few limitations exist in this study. The first limitation is related to the number of datasets. In the field of marketing field, it is often recommended to have a larger scale of data. Current number of responses would be considered as small samples. Henceforth, the results obtained are confined to the interpretation of existing sample. Future researchers are recommended to adopt current research model by expanding on the sample size to beyond 1,000 in order to examine on a larger number of digital consumers.

Apart from the sample size, current research focused on the gender group but has not explored other groupings such as the type of good and services (i.e., product-based grouping) purchased through online recommendation system, income level and regions of the digital consumers. It is believed that these groupings may portray different findings with specific details.

The findings derived from current research are very much state-of-art due to two main justifications. Firstly, the business world moves at a fast pace with the rapid advancement of digital technologies which disrupt sales and marketing channels. Secondly, at the juncture of the writing of this research, the global market is affected by Covid-19 pandemic. Many countries are practising partial or total lockdown which resulted in many online transactions. As such, a longitudinal study is recommended to understand the subject matter better. Besides, during the worldwide Covid-19 crisis, Yuen (2020) reported the cybersecurity cases has risen by 82.3%. This phenomenon further reinforces the importance of trust in the Internet ecosystem. Trust-based recommendation system would then be relevant in future research.

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