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ORIGINAL ARTICLE

How does risk interplay with trust in pre-and post-purchase intention to engage: PLS-SEM and ML classification approach

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Abstract

This study explores the effect of perceived risk PR and perceived affective and cognitive trust, PAT and PCT, respectively, on the intention to engage with Facebook FB adverts. Most of the literature explores the intention to engage pre-purchase, and only limited studies address all behavioral manifestations of the intention to engage -other than eWoM- post-purchase. In this study we explore the effect of PR, PAT and PCT on the intention to endorse, comment, and pass-on in the pre- and post-purchase when satisfied or dissatisfied. We collected quantitative data from young FB users in Southeast Asia, aged between 17 and 30. By supplementing the PLS-SEM analysis with accuracy scores resulting from classification-based machine learning (ML) algorithms, we explore the mediating effect of PR in the pre-purchase stage and its moderating effect in the post-purchase intention to engage. Our findings support the negative mediation effect of PR on the association between PAT and PCT and the intention to comment, and its positive mediation to endorse and share pre-purchase. Whereas the PR positive moderation effect is confirmed in the post-purchase intention to engage. The study proposes several academic and managerial implications.

Keywords Pre-purchase intention to engage · Post-purchase intention to engage · Cognitive trust · Affective trust · Perceived risk · Machine learning · Classification · Partial least squares structural equation modeling PLS-SEM

Introduction

Background and problem statement

Partial least square structural equation modeling PLS-SEM is one of the most applied analytical methods in social science research, including marketing (Sarstedt and Danks 2022). The importance of social science research lies in its ability to be generalized to form proper managerial implications (Sarstedt and Danks 2022). Even though in-sample fit indices– resulting from the conventional PLS-SEM analysis– are used as indicative of the model's predictive power, the managerial and practical implications of the SEM should be based on out-of-sample fit indices (Shmueli et al. 2016). With out-of-sample fit indices, the generalization of practical and managerial implications will be statistically indisputable and could be generalized across different samples, contexts, and time (Sarstedt and Danks 2022). For this purpose, the open-source package, *PLSPredict* (Shmueli et al. 2016), has become a standard in the PLS-SEM's analysis.

While the *PLSPredict* package provides a way to assess the model's predictive power, it does not quantify the model's predictive accuracy, meaning that, it does not result on a metric or a single score that could be used to accurately capture the true positives and negatives of the predictive model and thus judge its predictive performance. Evaluating the predictive accuracy of models is a vital step in model development (Abdelmoety et al. 2022; Fair 1986; Tedeschi 2006). It also assists in determining the suitability of a model for specific applications (e.g., Shehadeh et al. 2021; Sun et al 2021). Moreover, it provides basis for comparing different modeling techniques and competing models.

We apply our PLS-SEM and ML classification approach to study customer engagement behavior. Consumer

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behavior research has primarily focused on buying behavior and engagement. In the early 2000s, the marketing literature began studying customer engagement (Aboul-Dahab et al. 2021; Kumar 2013). Compared with customer loyalty and satisfaction, customer engagement may be "a relatively nascent" concept (Agag 2019; De Oliveira Santini et al. 2020), with more than twenty studies offering relevant but varying perspectives regarding the interplay of the relationship of perceived risk and trust to drive customer behavior (e.g., Usman et al. 2024; Munikrishnan et al. 2023; Alrawad et al. 2023a, b; Esawe 2022; Aslami et al. 2022). Appendix I summarizes twenty studies reflecting the literature's perspectives on different PLS-SEM configurations addressing perceived risk and trust in customer behavior research, including customer engagement.

Contrasting perspectives in outlining the relationship between perceived risk and trust and their effect on customer behavior, provide bases for more than three different PLS structural configurations or structural outlines to address the interplay of the relationship between perceived risk and trust to drive customer engagement behavior. First, some structural models hypothesize that perceived risk affects perceived trust, and they both affect behavioral intention (e.g., Munikrishnan et al. 2023; Alrawad et al. 2023a, b; Almaiah et al. 2023; Amnas et al. 2023; Aslami et al. 2022; Abror et al. 2022; Kindangen et al. 2021; Sari et al. 2020; Taşkın and Taşkın, 2019; Ejdys et al. 2019; Hoque and Alam 2018; Ho et al. 2017). Another group of studies suggest that perceived risk and trust both affect the behavioral intention with no relationship between them (e.g., Agag et al. 2020; Usman et al. 2024; Widyanto et al. 2022; Amarullah et al. 2022; Habib and Hamadneh 2021; López-Zambrano et al. 2021; Hasan et al. 2021), while a third group of studies hypothesize that perceived trust affects perceived risk and they both affect behavioral intentions (e.g., Agag and Eid 2020; Esawe 2022; Hasan et al. 2021; Ventre and Kolbe 2020; Marriott and Williams 2018). The last group hypothesize moderating effects of these two constructs in varying ways (e.g., Khan and Abideen 2023; Qalati et al. 2021).

We argue that, when faced with contrasting structural configurations, as in the case of the relationship between perceived risk and trust, PLS-SEM analysis alone does not facilitate a fully informed model selection process. By supplementing PLS-SEM with ML classification, we are able to obtain a model's accuracy score -along other metrics– that could guide the selection process. Our study addresses this gap and extends prior research by focusing on the interplay of the relationship between perceived risk and trust to drive customer engagement pre- and post-purchase when satisfied or dissatisfied. We achieve this by extending the operationalization of perceived trust into its cognitive and affective components.

Literature gaps in the theoretical models

The literature highlights the role of perceived risk and trust as common antecedents of consumer behavioral intention (Hsu and Lin 2020; Dessart 2017), and as important factors affecting customer engagement (Agag et al. 2023a; Kim et al. 2019; Levy and Gvili 2015). For example, through a meta-analysis approach, Lăzăroiu et al. (2020) confirmed the importance of examining the role of trust and perceived risk together in driving consumer engagement, particularly in social commerce. They presented evidence that consumers' decision-making process is described by "dynamic performance" with a need to consider all stages of the customer's journey including pre- and post-purchase behaviors. However, they did not address the interplay of the relationship of both constructs in post-purchase or compared between pre- and post-purchase dynamics and outcomes. In a relevant vein, the findings of de Oliveira Santini (2020) confirmed the importance of satisfaction and trust to drive engagement but did not examine how the relationships among these factors interplay in possibly a different way when the customer is satisfied vs. dissatisfied post-purchase. Moreover, there is very limited literature examining the effect of perceived risk and trust on post-purchase intention to engage (Ramkumar et al., 2019), particularly, the intention to engage with Facebook FB adverts when satisfied or dissatisfied (Agag et al. 2023b; Ho et al. 2022).

To address the aforementioned knowledge gaps, based on a concrete theoretical foundation surrounding the post-purchase intention to engage, we propose the positive moderating effect of initial perceived risk on the positive effect of perceived affective and cognitive trust on the intention to engage post-purchase when satisfied or dissatisfied. With regards to the pre-purchase intention to engage, and based on concrete theoretical basis, we propose that perceived affective and cognitive trust negatively affect perceived risk and they both positively affect the intention to engage pre-purchase.

Research objectives and novelty

This study strives to address the gaps in the literature by answering the following research questions:

RQ-1 How does perceived risk plays a role with perceived affective and cognitive trust to predict the pre- and post-purchase intention to engage.

RQ-2 How can we apply classification-based ML algorithms to identify the mediation structural model that outperforms alternative models in predicting the pre-purchase intention to engage.

RQ-3 How to compare the moderating effect of perceived risk on the relationship of perceived affective and cognitive trust and the post–purchase intention to engage when the customer is satisfied vs. dissatisfied.

Regarding the novelty of our study, first, to the best of our knowledge, there is a scarcity of studies in social sciences that address the use of PLS-SEM with classification ML algorithms to produce an accuracy score in mediation and moderation analysis. We group SEM-ML blended studies in three groups. First, studies that discussed the idea of applying machine learning for prediction as a supplementary practice in SEM. For example, Sarstedt and Danks (2022) discussed the necessity of using out-of-sample fit indices to produce managerial implications in Human Resource literature. Richter et al. (2022) lightly mentioned machine learning in their paper's section, "Triangulating PLS-SEM with Other Methods/Techniques".

The second group consists of studies that applied different machine learning ML approaches to management and marketing-related areas. For example, Arshi et al. (2021) used the train-test split approach to predict the effect of the independent variables on entrepreneurial behavior with only one dataset for validation. Zobair et al. (2021) evaluated their questionnaire empirically and validated the proposed research model and hypotheses using a two-staged PLS-SEM and deep neural network machine learning for detecting both linear and non-linear relationships. Elnagar et al. (2022) predicted the intention to use a smartwatch by applying machine learning algorithms using Weka.

The third group encompasses studies that focused on developing technical extensions of SEM based on machine learning techniques. For example, van Kesteren and Oberski (2022) introduced three SEM extensions. Our study belongs to the second group of research, we employ six different classification ML algorithms to validate whether predictive latent variables in the PLS model predict the response latent variable with an acceptable accuracy score or not.

This study aims to contribute through demonstrating that: (i) the accuracy score of the PLS model can be obtained by applying classification- ML algorithms. Accuracy scores above the conventional threshold of 0.75 can be considered to accurately predict the dependent variable and thus be applied for models' selection problems. A consistency analysis between the PLS-SEM metrics (in-sample and out-of-sample) compared to the accuracy scores of the classification-based ML supports the suitability of using the accuracy score metric for model selection in mediation analysis. (ii) We recommend that, in moderation analysis, the accuracy scores of the classification-based ML algorithms of low vs. high engagement datasets be compared for verification.

Second, regarding the novelty of the theoretical framework, as far as we know, research studies examining the effect of both perceived risk and trust on the pre- and post-purchase intention to engage in one study is very rare despite the importance of both constructs over all stages of the customer journey (Agag et al. 2024a; Lăzăroiu et al. 2020). We contribute by utilizing classification-based ML algorithms along with the conventional PLS-SEM method of analysis to: (i) test perceived risk mediation effect on the association between trust (cognitive and affective) and pre-purchase intention to engage against other contrasting models proposed in the literature; (ii) we also test the moderation effect of perceived risk on the association of trust (cognitive and affective) and the post-purchase intention to engage when satisfied vs. dissatisfied.

This paper aims at exploring the relationship of perceived risk and trust (affective and cognitive) and their effect on the intention to engage (pre-purchase and post-purchase) by supplementing the PLS-SEM method with an accuracy score resulting from classification-based ML algorithms. This methodological approach enables researchers to compare the predictive accuracy of different latent endogenous variables in moderation PLS analysis and also mediation PLS models with other alternative or contrasting models. The study focuses on capturing initial trust and perceived risk at the first impression of interacting with FB adverts of unfamiliar brands (Agag et al. 2024b; Martinelli Watanuki and de Oliveira Moraes 2024; Zhang et al. 2019). Similarly, Moriuchi and Takahashi (2023) studied initial trust in social commerce and emphasized the role of trust toward a platform or a seller differs based on the cognitive or functional value and the emotional or affective value.

This paper is organized as follows; the next section represents literature on the study's variables and theories. Chapter 3 outlines the theoretical framework and hypotheses development. In chapter 4, we describe our data collection and measures. Finally, we describe and discuss the findings, and propose managerial and theoretical implications. The study is concluded with limitations and possible future research.

Literature review

Intention to engage with Facebook advertisements

FB content takes various forms, including text, images, videos, and links. FB offers various Ad types: still image ads, video ads, slideshow and carousel ads, dynamic ads that allow for remarketing, leads and poll ads, stories ads and augmented reality ads, and messenger ads. We limit our investigation to all types of ads appearing on the user's profile home, excluding, for example, messenger ads.

Engagement is defined differently in the literature. Vivek et al. (2012; p.133) considered the exchange of knowledge as the core of engagement; they defined customer engagement based on the intensity of individual participation and the level of connection with the brand's activities.

Customer-brand engagement is also defined as a multidimensional concept aimed at creating a brand experience (Ho et al. 2022). Engagement is regarded as a high-order construct composed of first-order variables that consider different consumer experiences (Agag and El-Masry 2016; Mersey et al. 2010). Brodie et al. (2013) suggested an experiential and behavioral dual approach to engagement. With this experiential-based view and definition of engagement, the customer engagement behavioral responses that are represented in clicks, likes, shares, and comments (Agag et al. 2019; Moran et al. 2020) are considered as consequences of engagement and not part of the customer-brand engagement construct (Triantafillidou and Siomkos 2018; Syrdal and Briggs 2016).

Ananda et al. (2019) categorized engagement behaviors as either pass-on or recommendation behavior (e.g., "sharing" or "retweeting") or endorsing behavior (e.g., "liking," "loving" or "favoring"). Depending on the design functionalities of the social media platform, we can refer, for example, to retweets and replies on Twitter, and likes, shares, and comments on FB and Instagram (Agag et al. 2024c; Hoffman and Fodor 2010). Van Doorn et al. (2010) suggested that customer engagement behaviors are defined through behavioral manifestations with a brand focus. The reports generated by various analytics tools for measuring the level of engagement on social networks are mainly based on the different types of followers' interaction; for example, views, likes, shares, and comments (Kite et al. 2019).

Accordingly, the following behavioral engagement manifestations are considered in this study: (i) expressing interest by endorsing the brand by either pressing the "like" button on a brand's post or advert, or the "follow" button on the brand's FB page; (ii) recommending and passing on brand-related content by pressing the 'share' button on a brand's FB story, post, or advert; (iii) giving feedback by "commenting" on a brand's advert, or post. We synthesize the intention to engage by adopting the observed items considered in previous studies and covers the three main categories of engaging behavior that contributes to the FB ad's efficacy (Aldossary et al. 2024; Sharma and Lulandala 2021; Shaalan et al. 2022; Solem 2016).

Venkatesan (2017) explains that engagement in pre-purchase and post-purchase in the following stages: customer acquisition stage, retention stage, growth stage, and win-back. In this study, we focus on the customer acquisition stage, as shown by the systematic literature review of Phan et al. (2021), examining pre-purchase and post-purchase behavior in e-commerce is not greatly explored in the literature. Liu et al. (2020) suggested that individual reviews are more important in the post-purchase stage. We thus define our dependent (response) latent variables in this study as follows: pre-purchase intention to engage, post-purchase intention to engage. At the post-purchase intention to engage, customers engage when they are satisfied or dissatisfied. In this study we refer to these two constructs as a satisfied post-purchase and dissatisfied post-purchase intention to engage.

Theoretical foundations to understand trust

We base our theoretical foundation to understand the relationship between trust and customer engagement behavior on the following theories: Trust transfer theory, theory of crowd capital, and the attribution theory. Trust transfer theory is used to operationalize trust into its two main components: affective and cognitive. The theory of crowd capital paves the theoretical foundation to define and understand affective trust, while the attribution theory explains cognitive trust. According to the trust transfer theory (Shehawy et al. 2024; Stewart 2003), trust in social commerce can be derived as a result of mutual associations (Chiu et al. 2024; Hsu and Hu 2024). According to this theory, trust should be examined by two key mechanisms; cognitive-based trust and affective-based trust (Alghamdi and Agag 2023a; McKnight et al. 1998). In line with this notion, McAllister (1995) define trust as a blend of perceived cognitive and affective components. There is an agreement that the notion of engagement constitutes of cognitive, affective, and behavioral dimensions (Algharabat et al. 2020). In this vein, cognitive, affective, and behavioral dimensions should be considered when defining trust.

Balaji et al. (2023) define trust in consumers' generated content on social media as the willingness to depend on other members' actions, reviews, and such to make decisions. Social media trust refers to building trust in a social context via motivating users' interaction in specific social network platforms (Algharabat and Rana 2021). Perceived affective trust PAT is defined as that evolving from emotional basis with other individuals on an online network, it emerges from the social or affectionate bonds among individuals. PAT is developed from indirect sources such as word-of-mouth and peripheral cues (Alghamdi and Agag 2023b; Li et al. 2021).

The theory of crowd capital (Prpic and Shukla 2013) helps explain the effect of bandwagon cues on the perception of trust. The bandwagon cues are "system aggregated information about the crowd behavior or peer endorsement displayed on a web interface (e.g., the number of likes on a Facebook post)." (Wang et al. 2023). The theory of crowd capital studies the crowd's ability to influence the individual's behavior; various researchers in different areas have utilized this theory in studying social commerce. For example, Yin et al. (2019) investigated the impact of the active participation of the crowd on the number of financial funds obtained by a project through a machine learning approach.

Liu et al. (2024) explored factors determining the intention of leaving either positive feedback or negative (eWoM) on social media with focus on platform symmetry. On the other hand, Zhang et al. (2017) investigated the role of family as a closer crowd circle to influence the intention of generation Y to engage. Similarly, Whiting et al. (2019) followed a qualitative approach to study customer engagement, manifested by leaving positive or negative (eWoM).

The crowd engagement concept captures customers' entire possibilities of behavioral actions with a brand. People are affected by others' opinions, perceptions, and verdicts (Srivastava and Sivaramakrishnan 2021; Kim et al. 2019). More specifically, social media users are highly influenced by their relatives' and friends' comments and recommendations (Ou et al. 2022). The engaging behavior of close friends on FB contributes to forming trust. Lee et al. (2015) studied the effect of friends' reviews and movie ratings on the individual's own movie rating; they observed a positive effect of friends' ratings on the individual's movie rating. Algharabat and Rana (2021) reported similar results in community engagement.

Cognitive-based trust is developed through direct interactions with the ecommerce platform (Li et al. 2021). Perceived cognitive trust PCT evolves from the early purchase journey, during which the consumer holds no prior perception of the brand or company. In the context of social media, the customer's in-depth examination of the intrinsic characteristics of the FB advert is part of the process that forms the components of cognitive trust (Alsuwaidi et al. 2022; Nieuwenhuis 2020). PCT entails using analysis and evidence to form an assessment (McAllister 1995); this implies reaching the judgment that the trustee will highly likely fulfill the expectations. The overall content of the advert is one of the main components assessed (Dolan et al. 2019), and the characteristics of the brand's FB posts and adverts are a source of information that forms the components of PCT (Alyahya et al. 2023a; Irshad et al. 2020).

We utilize the attribution theory to understand how cognitive trust components affect the intention to engage online (Shaver 2016). The attribution theory is concerned with understanding individuals' casual justifications for incidents and the individuals' perceptions and judgments of 'the other.' The theory's assumption, as applied to FB, is that an individual can evaluate a considerably vast volume of information about numerous FB comments in multiple posts or adverts at different points in time to reach a specific attribution. For example, based on a shared understanding of the attribution theory, while customers browse a brand's FB page or view a FB advert, they evaluate the product's quality and cost and attribute the brand's value. The outcome of such evaluations impacts the behavioral intention by either inciting or dimming interest in it.

The elements and features of a website, such as videos, images, content, and symbols, affect the customers' attitudes. Hwang et al. (2011) studied PAT and PCT in hospitality; they examined the role of high-quality website design and online adverts in forming cognitive trust. Another intrinsic characteristic of an advert is the language of the message. Nantel and Glaser (2008) suggested a strong association between the mother tongue language with usability. Similar findings are described in the usability of mobile health apps (Gagnon et al. 2024). The FB advert is also attributed to the components of its main text, including emojis (Alyahya et al. 2023b; Bai et al. 2019). Based on this literature, we synthesize cognitive trust by examining: (i) visual media as in images and videos, (ii) the use of emojis in the main text of the FB advert, (iii) the appropriate language of the FB advert, and (iv) the overall quality perception of the brand's external website.

Theory of perceived risk

The audience may be entertained by FB adverts, especially when interactivity, storytelling, and advanced multimedia are embedded in the design. Conversely, advertisements may also be annoying and confusing or pose a perceived risk PR. Consumer's perceived risk was originally theorized by Bauer (1960) as the undesirable outcome that a consumer anticipates that it can follow his current actions. Mitchell (1999) divides it into two components: uncertainty about the consequences of a wrong choice and uncertainty about the outcome. Perceived risk in e-commerce is also defined as the likelihood that the product will fail to provide the expected benefits (Roselius 1971).

Researchers extensively utilized the perceived risk theory to explain consumer behaviors, including customer engagement (Srivastava and Sivaramakrishnan 2021; Mitchell 1992). Risk involves an element of uncertainty and, thus, is related to costs. Perceived risk is generally defined as a "subjectively determined expectation of loss" (Mitchell 1999, p.168). Loss or costs are not limited to monetary value but also involve all sorts of efforts (Alyahya et al. 2023c; Shehawy et al. 2018; Wood et al. 2021; Youssef et al. 2022; Zeithaml 2018).

Several scholars have developed and refined the perceived risk PR theory (Alyahya et al. 2022; Mitchell and Greatorex 1988), whereby the concept of perceived risk is considered multidimensional and has different facets. For example, PR was studied by considering psychological risk and performance risk (Cunningham, 2005). PR can also be categorized as functional, physical, financial, time, psychological, and social (Alzaidi and Agag 2022; Schiffman and Kanuk 1994). In the context of e-commerce, researchers considered PR to comprise financial, social, product, physical, performance, temporal or time risk (Deng and Ritchie 2018; Eid et al. 2020; Olya and Al-ansi 2018). In the context of engagement with FB adverts, we synthesize PR by considering relevant risk components, we refer to Appendix II for perceived risk dimensions and their relationships with trust components and engagement.

Theoretical framework and hypotheses development

Affective and cognitive trust and the pre- and post-purchase intention to engage

Drawing on the theory of trust transfer and the theory of crowd capital and research in the area of customer engagement on social media platforms, the more followers a brand's FB page has, the greater the perceived brand value and, thus, the greater the perceived trust (Eid et al. 2019; Sharma et al. 2017). Algharabat and Rana (2021) shows that community trust has a positive impact on brand engagement. Moreover, different crowd engagement behaviors, as in the number of likes and comments, indicate the post's popularity or the FB advert's brand (Reimer 2023). The effect of influential personalities like social media stars and public celebrities and other known social media influencers also contribute to forming trust (Shafiq et al. 2023). The findings of Mainolfi and Vergura (2022) indicated fashion bloggers' positive influence on the blog's engagement. In the trust literature, trust in e-commerce can be studied in two distinct stages: pre-purchase and post-purchase (Gautam 2024). Similarly, in the context of international online outshopping, Ramkumar and Ellie Jin (2019) studied the impact of trust in two phases: pre-purchase and post-purchase. In addition, a few e-commerce studies have empirically examined the impact of trust on behavioral intentions in the pre- and post-purchase stages (e.g., Senachai et al. 2024; Gautam 2024; Matić Šošić and Vojvodić, 2023; Sullivan and Kim 2018). Thus, we propose the following hypotheses:

$\boldsymbol{H_1}$: PAT positively affect the pre-purchase intention to engage by ($\boldsymbol{H_1}$-a) commenting to obtain feedback, ($\boldsymbol{H_1}$-b) liking and following to endorse the brand, and ($\boldsymbol{H_1}$-c) sharing to recommend the brand.

$\boldsymbol{H_2}$: PAT positively affect the satisfied post-purchase intention to engage by ($\boldsymbol{H_2}$-a) commenting to provide feedback on the experience with the brand, ($\boldsymbol{H_2}$-b) liking and following to endorse the brand, and ($\boldsymbol{H_2}$-c) sharing to recommend the brand.

$\boldsymbol{H_3}$: PAT positively affect the dissatisfied post-purchase intention to engage by ($\boldsymbol{H_3}$-a) negatively commenting to provide feedback on the experience with the brand, ($\boldsymbol{H_3}$-b) sharing negative posts about the brand.

Valuable content on social media drives user engagement (Dolan et al. 2019). Overall, interactivity and rich media are major technology affordances that influence users' participation behavior on social media (Shao and Pan 2019). The features and design aspects such as images, impact the users' evaluation of the quality of the advertised products and thus, their intention to engage (Moran et al. 2020). Research studies in digital marketing suggest that defectively designed advertisements fail to compete for the attention of prospective customers (Simola et al. 2011), thus losing chances to engage with them (Shahbaznezhad et al. 2021). The formation of trust and an online behavioral intention to engage was explored by recent research (Samarah et al. 2022; Algharabat and Rana 2021; Sharma and Lulandala 2021; Cao et al. 2021). However, little research efforts in social commerce have empirically tested the effect of perceived trust, particularly cognitive trust, on the intention to engage or on behavioral intentions in general in the pre- and post-purchase stages. Thus, we propose the following hypotheses:

$\boldsymbol{H_4}$: PCT positively affect the pre-purchase intention to engage by ($\boldsymbol{H_4}$-a) commenting to obtain feedback, ($\boldsymbol{H_4}$-b) liking and following to endorse the brand, and ($\boldsymbol{H_4}$-c) sharing to recommend the brand.

$\boldsymbol{H_5}$: PCT positively affect the satisfied post-purchase intention to engage by ($\boldsymbol{H_5}$-a) commenting to provide feedback on the experience with the brand, ($\boldsymbol{H_5}$-b) liking and following to endorse the brand, and ($\boldsymbol{H_5}$-c) sharing to recommend the brand.

$\boldsymbol{H_6}$: PCT positively affect the dissatisfied post-purchase intention to engage by ($\boldsymbol{H_6}$-a) negatively commenting to provide feedback on the experience with the brand, ($\boldsymbol{H_6}$-b) sharing negative posts about the brand.

Perceived risk and the pre-purchase intention to engage

PR is believed to greatly impact the pre-purchase consumer's buying process (Srivastava et al. 2021; Park and Tussyadiah 2017; Mitchell 1992). Consumers purposely view online purchasing as a threat (Ariff et al. 2014). By nature, individuals attempt to reach an acceptable level of certainty and diminish or avoid uncertainty. Therefore, when faced with risk, consumers will take various actions to reduce it (Ting et al. 2010). For example, customers seek information to minimize risk in the pre-purchase stage (Gunawan and Septianie 2021). They resort to social media platforms, like leaving their inquiries by commenting on FB adverts to mitigate risk (Haworth et al. 2015).

Although PR negatively affects the intention to purchase or travel (Rather 2021), nowadays, more consumers tolerate online risk and don’t resort to risk avoidance (Farley and Murched 2016). For example, more consumers in India are keener to engage with FB adverts regardless of their intention to purchase (Sharma and Lulandala 2021). This is because consumers have a higher propensity to risk-taking in the pre-purchase stage when it is motivated by risk minimization (Ha 2002). Therefore, perceived risk is believed to positively impact the customer’s intention to engage with a FB advert through commenting to request feedback.

H_7: PR positively affects the pre-purchase intention to engage by commenting to obtain feedback.

FB users associate themselves with the brands they endorse or recommend; for them, it is an implicit way of building an image and self-expression (Santini et al. 2020). Furthermore, sharing FB adverts with high-risk content that carries possible false information or defamation affect the FB user’s reputation (Demek et al. 2018). Therefore, perceived risk is expected to have a negative effect on recommendation and endorsing behavior pre-purchase. We thus propose the following hypotheses for the pre-purchase engaging behaviors:

H_8: PR negatively affect the pre-purchase intention to engage by (***H_8***-a) liking and following to endorse the brand, and (***H_8***-b) sharing to recommend the brand.

The relationship between perceived risk and trust

Pre-purchase intention to engage model

Several structural models hypothesize that perceived trust affects PR and they both affect behavioral intentions (e.g., Elhoushy et al. 2020; Seo and Lee 2021; Ventre and Kolbe 2020; Vohra and Bhardwaj 2019; Marriott and Williams 2018). PCT and PAT are built over time (Elbaz et al. 2018; Vanneste et al. 2014). Each single incident of interaction with a FB advert is surrounded with a certain level of uncertainty (Srivastava et al. 2021). In the context of social media, Fan et al. (2022) showed that perceived trust affects PR and they both affect customer engagement behavior in social commerce.

Sánchez-Alzate and Sánchez-Torres (2017) confirmed the mitigating effect of social influence (defined here within PAT) on PR, whereby social influence is defined as the influence of people’s opinion— even if they go against the views of the decision-maker. This social influence represents the negative association of PAT on PR. PAT also allows for possible consumer-consumer interaction, Xue et al. (2020) demonstrated that such a construct representing PAT negatively affects PR, which in turn negatively affects social commerce engagement. Moreover, Xue et al. (2020) studied the effect of social content representing PCT on PR in the context of social commerce engagement. In their study, they investigated personalization and found that, the higher the quality of the characteristics and features of the FB post, the higher its effect on mitigating PR (Elbeltagi and Agag 2016; Xue et al. 2020; Dolan et al. 2019; Shao and Pan 2019). Thus, we hypothesize the following for the effect of perceived trust on PR in the pre-purchase intention to endorse and pass-on model:

H_9: PAT negatively affects PR in the pre-purchase intention to engage with FB adverts (endorse and pass-on).

H_{10}: PCT negatively affects PR in the pre-purchase intention to engage with FB adverts (endorse and pass-on).

However, the literature also contains alternative models. Some models proposed that PR affects perceived trust, and they both affect behavioral intention (e.g., Sari et al. 2020; Zhang et al. 2019; Hoque and Alam 2018; Ho et al. 2017). Other studies suggest that PR and perceived trust both affect the behavioral intention with no relationship between them (e.g., Habib and Hamadneh 2021).

The post-purchase intention to engage model

While PR has been thoroughly studied as a deterministic factor of customer's behavioral intention in the pre-purchase state (Marriott and Williams 2018), it was also found to play a crucial part in the post-purchase experience (Hsiao 2021). In the pre-purchase stage, customers develop a certain level of expectations. When the service/product’s consumption experience meets or exceeds the expectations in the pre-purchase stage, a state of satisfaction or dissatisfaction is experienced (Patricks et al. 2020). With the presence of PR, such expectations are surrounded with much uncertainty that brings down the expectations and thus yield to a higher level of satisfaction when the expectations are met in the post-purchase stage (Bernarto and Purwanto 2022). The psychological need for fulling self-esteem in Maslow’s hierarchy of needs explains the need to share a positive behavioral engagement about positive experiences as successful risk-taking incidents (Vithayaporn et al. 2022). Therefore, when customers are satisfied, they are more willing to engage (de Oliveira Santini et al. 2020; Direction 2012) to share their positive experiences with their network (Vithayaporn et al. 2022). Therefore, engaged customers are likely to share their experiences, provide feedback and recommend the product/service.

When the customer’s expectations are not met in the post-purchase stage, this results in dissatisfaction (Hamdy et al. 2024; Oliveira et al. 2022). In this case, customers are more likely to engage in negative communication about the brand; negative comments are also considered part of the e-WoM. Such communications are often motivated by venting anger or seeking revenge (Yang et al. 2022) and warning

FB friends. Customers could share a post with friends about this negative experience.

Kim et al. (2008) revealed that consumer post-purchase satisfaction is significantly related to e-commerce trust. Existing studies commonly define satisfaction as an "emotional state from post-purchase feeling" (Laradi et al. 2024; Williams and Soutar 2009). However, a uniform definition of consumer satisfaction is "summary affective response of varying intensity…" toward a certain product or service (Giese and Cote 2000). This varying intensity is affected by various factors including PR (Selim et al. 2022; Wu et al. 2021). PR has been shown to moderate the relationship between the effect of satisfaction on the continuance intentional behavior (Lho et al. 2022). The more the confirmed pre-purchase uncertainties or PR in favor of the product/service, the higher the satisfaction, while when more PR is unfavorably confirmed, the higher the resulting dissatisfaction (Akram et al. 2019). This feeling of satisfaction with a product or service is found to affect the intention to engage (Majeed et al 2022). Likewise, dissatisfaction with the product experience results on a higher intention to engage as in sharing negative eWoM (Liu and Jayawardhena 2023). Accordingly, we assume the following:

$\boldsymbol{H}_{11}$: PR positively moderates the association between PCT and satisfied post-purchase intention to engage ($\boldsymbol{H}_{11}$-a) commenting to give positive feedback, ($\boldsymbol{H}_{11}$-b) endorsing by liking the advert, and ($\boldsymbol{H}_{11}$-c) sharing positive posts about the brand.

$\boldsymbol{H}_{12}$: PR positively moderates the relationship on the association between PAT and satisfied post-purchase intention to engage ($\boldsymbol{H}_{12}$-a) commenting to give positive feedback, ($\boldsymbol{H}_{12}$-b) endorsing by liking the advert, and ($\boldsymbol{H}_{12}$-c) sharing positive posts about the brand.

$\boldsymbol{H}_{13}$: PR positively moderates the relationship on the association between PCT and dissatisfied post-purchase intention to engage ($\boldsymbol{H}_{13}$-a) commenting to give negative feedback, and ($\boldsymbol{H}_{13}$-b) sharing negative posts about the brand.

$\boldsymbol{H}_{14}$: PR positively moderates the relationship on the association between PAT and dissatisfied post-purchase intention to engage ($\boldsymbol{H}_{13}$-a) commenting to give negative feedback, and ($\boldsymbol{H}_{13}$-b) sharing negative posts about the brand.

Methodology

Study design

This study consists of four main stages. In the first stage, we follow the PLS-SEM method using *SmartPLS* software. We first examine the reliability and validity of the measurement model and the common method bias. We also examine the in-sample fit indices of the structural models (A, B, and C) shown in Fig. 1.

In the second stage, we perform mediation analyses by carefully following the standard guidelines for evaluating mediation effects (Zhao et al. 2010; Preacher and Hayes 2008). We use the bootstrapping procedure with 5,000 subsamples with replacement (Carrión et al. 2017). Accordingly, testing the mediation effect is based on the total effect (TE), direct effect (DE), and indirect effect (IE).

For post-purchase intention to engage, we examine the moderating role of PR by carefully following the guidelines in (Hair et al. 2022). To compute the moderation results, *SmartPLS* performs the two-stage approach (Becker et al. 2023). In the third stage, we apply *PLSPredict* package developed by Shmueli et al. (2016). In the fourth stage, we apply classification-based machine learning algorithms to quantify the predictive power of the PLS models. In this stage, we test the hypothesis of whether the independent predictive latent variables predict the dependent response latent variable(s) with a sufficient accuracy score or not. To

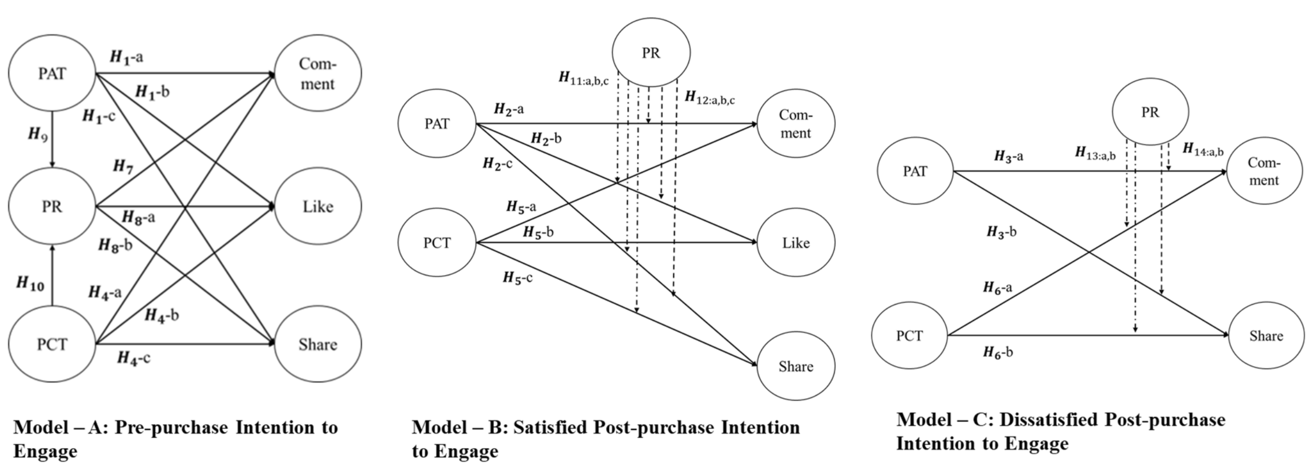
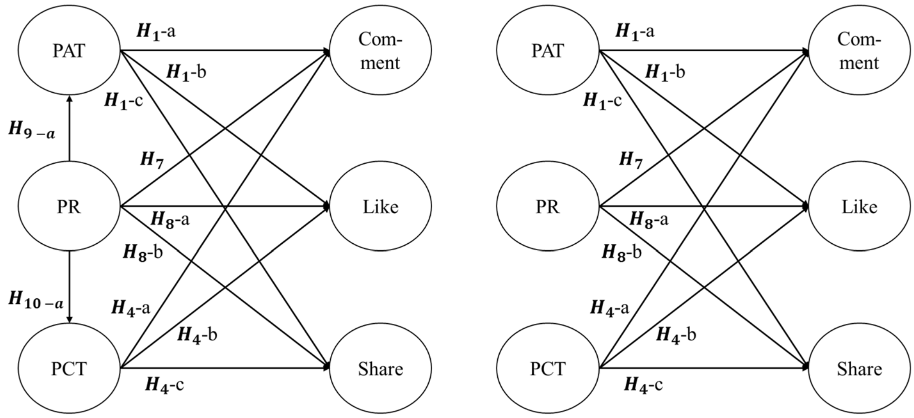


Fig. 1 Structural models of the study. *PAT* perceived affective trust, *PR* perceived risk, *PCT* perceived cognitive trust

Fig. 2 Alternative models of the relationship between perceived risk and trust in the pre-purchase intention to engage



Model – A-i: Pre-purchase Intention to Engage – PAT and PCT as Mediators

Model – A-ii: Pre-purchase Intention to Engage – No Mediation

examine the predictive accuracy of the classification models, we inspect the performance metrics computed from the resulting confusion matrix. We follow the rule of thumb in machine learning, where we consider the highest precision subject to a recall value of 0.75 (as in: Sharkasi et al. 2015). Lastly, we compare the accuracy scores of the alternative mediation models shown in Fig. 2. The purpose of this comparison is to confirm the suitability of the proposed model despite the conflicting literature about the relationship between PR and trust in the pre-purchase intentional behavior.

Measures and data collection instrument

The independent constructs (PR, PAT and PCT) are measured by four observed items or more that had been validated previously and modified slightly to fit the specific context of this study (see Table 1 for detailed description and sources). The pre-purchase intention to engage is measured by three behavioral actions on FB (Comment, endorse, and pass-on) based on the measurement scales used by Moran et al. (2020); Ananda et al. (2019); and Sharma and Lulandala (2021). The intention to comment pre-purchase is captured by: (i) commenting on interesting ads on FB, (ii) commenting with inquiries about the product/service, (iii) intention to use a FB advert. The intention to endorse an FB advert pre-purchase is captured by the following: (i) intention to like an FB advert, (ii) intention to endorse and support a brand I like on FB, (iii) intention to follow the FB page of an interesting brand. Finally, the intention to pass-on a FB advert pre-purchase is captured by: (i) intention to share interesting FB adverts with others, (ii) intention to recommend interesting brands promoted in FB adverts to friends and family, and (iii) intention to pass-on commercial and brand-related content to others. We capture initial perceived trust and risk by simplifying the conventional measurement scale as done by Pan et al. (2023), this is achieved semantically by using, for example, "I would be safe" in place of "I was safe" or "I feel safe".

A careful consideration is devoted to the questionnaire's language, question order, and context of the research, the questionnaire was disseminated in English targeting English-speaking participants. To capture the post-purchase intention to engage, we follow Zeithaml et al. (1993) and Oliver (1981) noted that predictive 'will be' expectations represent consumers' expectations about 'that will or is likely to happen in his/her next interaction'. The predicted expectation is 'based on past averaged performance … what the respondent feels performance will be' (Miller 1977, p. 76). We followed an established approach to capture the actual use in the post-purchase state (Horváth and Fedorko 2023; Nittala and Moturu 2023; Vidal-Ayuso et al. 2023). Valid participants confirmed commenting or sharing an FB advert after purchasing a product through FB in the past three months.

The first section of the questionnaire confirmed data collection from active FB users, it also explained the objective of the research, data privacy policy, and statement of ethics. The selection criteria of valid questionnaires is as follows: (i) being an active FB user, the first section of the survey captured data to confirm active use of FB and to estimate the average daily hours of FB use. (ii) shopping online, including FB on monthly basis, and (iii) agreeing to the terms of ethics. The second section of the questionnaire presented the five-point anchored scale questions to measure the observed items.

Sampling

A convenience sampling technique is used from international students at an international university in Tokyo city. The students were recruited through email (See, e.g., Krejcie and Morgan 1970). An email list of students, who have

Table 1 Description of the observed items of the model

Constructs and items	Description	References
Perceived risk (PR)		
PR 1	Delivery time uncertainty (temporal risk)	Ariff et al. (2014)
PR 2	Return the item for a replacement (product risk)	
PR 3	Information privacy risk (information risk)	
PR 4	Uncertainty of product meeting expectations (product risk)	
Perceived affective trust (PAT)		
PAT 1	Number of likes on (FB) advert	Yin et al. (2019)
PAT 2	Number of followers on (FB) page	
PAT 3	Comments on (FB) advert	
PAT 4	Influencer or celebrity featured in (FB) advert	
PAT 5	Close (FB) friend positive comments, shares and likes with the brand's (FB) advert	
Perceived cognitive trust (PCT)		
PCT 1	Quality of visual assets/marketing creatives	Dolan et al. (2019)
PCT 2	Use of icons and symbols in primary text of the (FB) advert	
PCT 3	Appropriate language of (FB) advert	
PCT 4	Quality of the brand's external website listed in the (FB) advert	
Pre-purchase intention to engage		
Comment to obtain feedback	Commenting on interesting ads on (FB)	Ananda et al. (2019)
	Commenting with inquiries about the product/service	
	Intention to use a FB advert	
Endorse	Intention to like an (FB) advert	
	Intention to endorse and support a brand I like on (FB)	
	Intention to follow the (FB) page of an interesting brand	
Pass-on	Intention to share interesting (FB) adverts with others	
	Intention to recommend interesting brands promoted in (FB) adverts to friends and family	
	Intention to pass-on commercial and brand-related content to others	
Satisfied post-purchase intention to engage		
Comment give feedback	Intention to leave a comment, assuming to receive an ad on your (FB) home about a product/service you were satisfied with	Ananda et al. (2019)
	Intention to give feedback about a purchase experience on a (FB) ad when satisfied	
Endorse	Intention to click like on a (FB) ad, given you have access to a (FB) ad promoting a brand/product you've been satisfied with	
	Intention to endorse and support a brand, given you have access to a (FB) ad promoting a brand/product you've been satisfied with	
	Intention to follow a (FB) page of a brand, you've been satisfied with	
Pass-on	Intention to share a (FB) ad with others, given you have access to a (FB) ad promoting a brand/product you've been satisfied with	
	Intention to recommend a brand/product you've been satisfied with to family and friends	
	Intention to pass-on content about a brand/product you've been satisfied with to others	
Dissatisfied post-purchase intention to engage		
Comment give feedback	Intention to leave a negative comment, assuming that you receive an ad on your (FB) page about a product/service you've been dissatisfied with	Ananda et al. (2019)
	Intention to give feedback about a bad purchase experience on (FB) when dissatisfied with your purchase	
Pass-on	Intention to share the (FB) ad with a post about your bad experience, given you have access to (FB) ad promoting a brand/product you've been dissatisfied with	
	Intention to not recommend a brand/product you've been dissatisfied with	
	Intention to pass-on negative content about a brand/product you've been dissatisfied with	

previously accepted to receive emails from the researcher to participate in future research studies, was anonymously utilized for this research. A total of 226 questionnaires were voluntarily completed during this period with a 35% response rate. After data cleaning and screening, a total of 209 questionnaires were valid for analysis. We also checked for biased responses; the data is thus clear of this concern. Based on Bentler and Chou's (1987) suggestion for a minimum subject-to-item ratio of 10:1 for confirmatory factory analysis, the sample size of 209 respondents seems to be sufficient. Moreover, based on a-priori sample size calculator for SEM, a sample size of 156 is considered sufficient. Thus, the sampling technique and the sample size are considered appropriate for measuring the intention to engage on FB. Regarding the general characteristics of the sample, Table 2 shows the sample's detailed profile.

The sample is made up of bachelor's and master's students between the ages of 17 and 30. Most of the sample (61.90%) is between 17 and 22 years old, and about 30% are between 22 and 27 years old. A 27% of the sample spends about 20–30% of monthly disposable income shopping online, including on FB. Regarding the sample adequacy for SEM, the Kaiser–Meyer–Olkin Measure of sampling adequacy yielded 0.823, and the chi-square of Bartlett's test of sphericity was significant (<0.001). This is an indication that the variables of the study are valid.

Table 2 Sample profile

Variable	Categories	Frequency	Percent
Gender	Male	81	38.57
	Female	129	61.43
Age	17–22	130	61.90
	22–27	64	30.48
	27–30	16	7.62
Daily hours on Facebook	≤ 1 h	97	46.19
	≤ 2 h	44	20.95
	≤ 3 h	41	19.52
	≤ 4 h	15	7.14
	≤ 5 h	13	6.19
Proportion of monthly online spent from disposable income	≤ 10%	100	47.62
	11–20%	58	27.62
	21– 30%	39	18.57
	> 30%	13	6.19
Country of origin	Vietnam	80	38.0
	Indonesia	40	19.0
	Thailand	37	17.6
	Japan	13	6.19
	Other (SEA)	40	19.0

SEA Southeast Asia

Common method bias

Common method bias (CMB) occurs when the variations in responses result from a biased design of the instrument; thus, the instrument fails to capture the genuine predispositions of the respondents. There are three main approaches to checking for bias, Harman's single-factor analysis (Williams et al. 2010), the common latent factor approach (Podsakoff et al. 2003), and the ad hoc marker variable technique (Lindell and Whitney 2001). First, we followed Harman's single-factor approach to examine CMB (Chang et al. 2010). With this approach, we evaluated the un-rotated factor solution to verify the factors responsible for the variance in all measured items; thus, we identified the amount of reliable error variance that is correlated between items (Williams et al. 2010). Our results of Harman's single-factor approach excluded the presence of CMB since any single factor explains a total of up to 26.023% of the variance, which is less than half of the total variance explained.

Second, we applied the common latent factor (CLF) test to examine CMB; the resulting squared values of the unstandardized path coefficient were all below 0.50, and the difference of the standardized regression weights from the CLF model compared to the model without the CLF are all less than 0.20. (Eichhorn 2014; Podsakoff et al. 2003). Third, to further verify the results, we also employed the CFA marker variable technique (Williams and O'Boyle 2015). When an ideal marker is considered, this technique detects the presence of CMB by 84% (Richardson et al. 2009), thus, making it the best choice for CMB examination. A marker variable was constructed with the following observed item: How fluent is your Japanese language? The question is highly unrelated to any of the constructs in our model. The unstandardized path coefficients of the CLF model with the added marker variable were below that of the coefficients resulting from the basic CLF approach without the marker variable; thus, this finding excludes the presence of a common method bias.

Analysis and results

The measurement models

Table 3 shows the general statistical characteristics of the study's variables. The loadings of the items on their respective variables are significant ranging between 0.710 to 0.995. We had to eliminate 'risk 1' because its loading was below 0.70; the loadings are considered satisfactory in the three models of this study. The composite reliability (CR) and Cronbach's alpha (α) scores in Table 3 ranged from 0.801 to 0.997 and 0.754 to 0.994, respectively. The minimum values of 0.801 and 0.754 are above the acceptable threshold of 0.70, which indicates that all variables are trustworthy. In

Table 3 Measurement statistics

Construct/indicators	Standard loadings			CR	VIF	(α)	AVE	t-statistic
	Pre-purchase I2E	Sat. post-purchase I2E	DisSat. post-purchase I2E					
Perceived affective trust (PAT)				0.895	1.080	0.842	0.683	
PAT 1	0.885	0.759	0.702					32.193
PAT 2	0.892	0.908	0.918					44.304
PAT 3	0.729	0.870	0.894					13.986
PAT 4	0.734	0.773	0.754					15.131
PAT 5	0.773	0.723	0.722					14.350
Perceived cognitive trust (PCT)				0.864	1.023	0.789	0.685	
PCT 1	0.806	0.989	0.809					3.997
PCT 2	0.710	0.753	0.895					4.227
PCT 3	0.898	0.711	0.898					6.574
PCT 4	0.731	0.795	0.730					4.973
Perceived risk (PR)				0.801	1.081	0.754	0.689	
PR 2	0.795	0.717	0.883					9.549
PR 3	0.802	0.793	0.772					12.819
PR 4	0.795	0.762	0.754					10.408
Pre-purchase intention to engage (Comment)				0.997	1.045	0.993	0.993	
Pre-purchase (Comment1)	0.940	–	–					48.230
Pre-purchase (Comment2)	0.979	–	–					25.566
Pre-purchase (Comment3)	0.853	–	–					34.444
Pre-purchase intention to engage (Endorse)				0.939	1.101	0.905	0.838	
Pre-purchase (Endorse1)	0.757	–	–					32.511
Pre-purchase (Endorse2)	0.981	–	–					45.284
Pre-purchase (Endorse3)	0.989	–	–					15.340
Pre-purchase intention to engage (Pass-on)				0.997	1.026	0.994	0.994	
Pre-purchase (Pass-on1)	0.703	–	–					27.623
Pre-purchase (Pass-on2)	0.995	–	–					25.414
Pre-purchase (Pass-on3)	0.703	–	–					20.589
Satisfied post-purchase intention to engage (Comment)				0.965	1.350	0.946	0.902	
Sat post-purchase (Comment1)	–	0.926	–					48.230
Sat post-purchase (Comment2)	–	0.975	–					25.566
Sat post-purchase (Comment3)	–	0.949	–					34.444
Satisfied post-purchase intention to engage (Endorse)				0.968	1.983	0.950	0.909	
Sat post-purchase (Endorse1)	–	0.934	–					32.511
Sat post-purchase (Endorse2)	–	0.978	–					45.284
Sat post-purchase (Endorse3)	–	0.949	–					15.340
Satisfied post-purchase intention to engage (Pass-on)				0.969	1.380	0.952	0.912	
Sat post-purchase (Pass-on1)	–	0.953	–					26.623
Sat post-purchase (Pass-on2)	–	0.979	–					24.414
Sat post-purchase (Pass-on3)	–	0.934	–					18.325
Dissatisfied post-purchase intention to engage (Comment)				0.969	1.349	0.953	0.913	
DisSat post-purchase (Comment1)	–	–	0.941					28.230
DisSat post-purchase (Comment2)	–	–	0.979					25.566
DisSat post-purchase (Comment3)	–	–	0.947					24.444
Dissatisfied post-purchase intention to engage (Pass-on)				0.910	1.378	0.953	0.910	
DisSat post-purchase (Pass-on1)	–	–	0.948					37.623
DisSat post-purchase (Pass-on2)	–	–	0.981					15.414
DisSat post-purchase (Pass-on3)	–	–	0.939					20.365

Table 3 (continued)

Sat. Satisfied, *DisSat.* dissatisfied

addition, the variance inflation factor (VIF) was less than 3.0 for all variables (Hair et al. 2021). Accordingly, no multicollinearity issues were detected.

As for convergent and discriminant validity, the values of the average variance extracted (AVE) are all higher than 0.5, which satisfies the threshold value suggested by Fornell and Larcker (1981). As shown in Table 4, evidence of discriminant validity was observed by (i) the values of AVE, which are larger than the corresponding squared between-construct correlations, and (ii) the heterotrait-monotrait ratio (HTMT) of study variables which are less than 0.85.

The structural models

The structural models of this study are evaluated based on the recommendations of Hair et al. (2021). The global fit indices of the three structural models are all acceptable. We report the results of the structural models outlined in Figure 1 in the following three sub-sections.

Model A: pre-purchase intention to engage and the mediating effect of perceived risk

Model Fit The model's SRMR value is $0.061 < 0.08$, thus, there is no evidence of model misspecification (Hu and Bentler 1999). The NFI values of 0.947; 0.945; and $0.926 > 0.90$, for pre-purchase comment, endorse, and pass-on, respectively are greater than 0.90, thus, the models fit the data well. The R-squared values of all constructs, reported in Table 5, are above 0.25 (Hair et al. 2011).

Hypotheses testing The estimated standardized path coefficients for the hypotheses and their significance are also reported in Table 5. The results of the pre-purchase intention to engage (I2E) model show that all the perceived risk's hypotheses H7 and H8 - a and b, are supported by ($\beta = 0.301$, f-square $= 0.271$, $\rho = 0.000$), ($\beta = -0.250$, f-square $= 0.197$, $\rho = 0.010$), and ($\beta = -0.300$, f-square $= 0.212$, $\rho = 0.037$), respectively.

As for PAT, all H1- a, -b, and -c hypotheses, which predict that PAT positively affect the intention to comment on, endorse and share an interesting product/service promoted by an FB advert, are supported by ($\beta = 0.140$,

Table 4 Discriminant validity

Constructs	(1)	(2)	(3)	(4)	(5)	(6)
Pre-purchase intention to engage model						
(1) Perceived affective trust	0.8270	0.1420	0.3430	0.0480	0.2870	0.1210
(2) Perceived cognitive trust	0.1140	0.8270	0.1440	0.0630	0.1820	0.1630
(3) Perceived risk	0.2290	0.0860	0.8300	0.0840	0.3800	0.3060
(4) Comment/feedback	0.0050	0.0200	0.0620	0.9970	0.0780	0.1910
(5) Endorse	0.2780	0.1870	0.2820	0.0660	0.9160	0.6480
(6) Pass-on	0.1130	0.1550	0.2270	0.1910	0.6330	0.9970
Satisfied post-purchase intention to engage model						
(1) Perceived affective trust	0.7880	0.1280	0.3760	0.1990	0.3560	0.3720
(2) Perceived cognitive trust	0.0750	0.7090	0.1370	0.0780	0.0550	0.0860
(3) Perceived risk	0.2770	0.0580	0.7580	0.2970	0.3590	0.3210
(4) Comment/feedback	0.1820	0.1200	0.2320	0.9500	0.5540	0.4940
(5) Endorse	0.3220	0.0630	0.2900	0.5260	0.9530	0.7240
(6) Pass-on	0.3400	0.1410	0.2560	0.4660	0.6870	0.9550
Dissatisfied post-purchase intention to engage model						
(1) Perceived affective trust	0.9560	0.7110	0.2200	0.0910	0.2420	
(2) Perceived cognitive trust	0.6780	0.9560	0.1250	0.1600	0.2160	
(3) Perceived risk	0.2140	0.1200	0.7850	0.0950	0.3330	
(4) Comment/feedback	0.0700	0.1280	0.0640	0.8530	0.1990	
(5) Pass-on	0.1800	0.1600	0.2210	0.1080	0.8300	

Note - i: The diagonal values are the squared root of the (AVE) of the latent variables and indicates the highest in any column or row

Note - ii: Elements below the diagonal represents the constructs' (HTMT) ratios

Table 5 Results of the hypotheses testing

Hypotheses of pre-purchase I2E model

	Path direction	Coefficients	*ρ*-value	*f*-square	Result
H1-a	PAT → pre-purchase I2E (Comment)	0.140	0.019	0.149	Supported
H1-b	PAT → pre-purchase I2E (Endorse)	0.198	0.000	0.153	Supported
H1-c	PAT → pre-purchase I2E (Pass-on)	0.410	0.021	0.220	Supported
H4-a	PCT → pre-purchase I2E (Comment)	0.186	0.002	0.169	Supported
H4-b	PCT → pre-purchase I2E (Endorse)	0.171	0.010	0.152	Supported
H4-c	PCT → pre-purchase I2E (Pass-on)	0.270	0.013	0.116	Supported
H7	PR → pre-purchase I2E (Comment)	0.301	0.000	0.271	Supported
H8-a	PR → pre-purchase I2E (Endorse)	-0.250	0.010	0.197	Supported
H8-b	PR → pre-purchase I2E (Pass-on)	-0.300	0.037	0.212	Supported
		R-square	*Q*-square		
	Pre-purchase I2E (Comment)	0.283	0.082		
	Pre-purchase I2E (Endorse)	0.285	0.046		
	Pre-purchase I2E (Pass-on)	0.257	0.058		

Hypotheses of satisfied post-purchase I2E model

	Path direction	Coefficients	ρ-value	*f*-square	Result
H2-a	PAT → satisfied post-purchase I2E (Comment)	*0.202*	*0.002*	*0.249*	Supported
H2-b	PAT → satisfied post-purchase I2E (Endorse)	*0.252*	*0.000*	*0.243*	Supported
H2-c	PAT → satisfied post-purchase I2E (Pass-on)	*0.275*	*0.005*	*0.182*	Supported
H5-a	PCT → satisfied post-purchase I2E (Comment)	0.122	0.025	0.016	Supported
H5-b	PCT → satisfied post-purchase I2E (Endorse)	0.159	0.027	0.104	Supported
H5-c	PCT → satisfied post-purchase I2E (Pass-on)	*0.134*	*0.032*	*0.210*	Supported
		R-square	*Q*-square		
	Satisfied post-purchase I2E (Comment)	0.286	0.168		
	Satisfied post-purchase I2E (Endorse)	0.259	0.126		
	Satisfied post-purchase I2E (Pass-on)	0.260	0.138		
		R-square	*Q*-square		
	Satisfied post-purchase I2E (Comment)	0.286	0.168		
	Satisfied post-purchase I2E (Endorse)	0.259	0.126		
	Satisfied post-purchase I2E (Pass-on)	0.260	0.138		

Hypotheses of dissatisfied post-purchase I2E model

	Path direction	Coefficients	ρ-value	*f*-square	Result
H3-a	PAT → dissatisfied post-purchase I2E (Comment)	0.176	0.009	0.152	Supported
H3-b	PAT → dissatisfied post-purchase I2E (pass-on)	0.175	0.024	0.206	Supported
H6-a	PCT → dissatisfied post-purchase I2E (Comment)	0.157	0.006	0.216	Supported
H6-b	PCT → dissatisfied post-purchase I2E (pass-on)	0.140	0.019	0.120	Supported
		R-square	*Q*-square		
	Dissatisfied post-purchase I2E (Comment)	0.270	0.094		
	Dissatisfied post-purchase I2E (pass-on)	0.252	0.020		
		R-square	*Q*-square		
	Dissatisfied post-purchase I2E (Comment)	0.270	0.094		
	Dissatisfied post-purchase I2E (pass-on)	0.252	0.020		

PR Perceived risk, *PAT* perceived affective trust, *PCT* perceived cognitive trust, *I2E* intention to engage *f*-square = 0.149, ρ = 0.019), (β = 0.198, *f*-square = 0.149, ρ = 0.000), and (β = 0.410, *f*-square = 0.220, ρ = 0.022), respectively.

Regarding the PCT, all hypotheses which predict that PCT positively affect the intention to comment, endorse, and share an interesting product/service promoted by a FB advert are supported by (β = 0.186, *f*-square = 0.169, ρ= 0.002), (β= 0.171, *f*-square = 0.152, ρ= 0.010), and (β= 0.270, *f*-square = 0.116, ρ= 0.013), respectively.

Mediation analysis In the pre-purchase intention to engage model (Model A in Fig. 1), the mediation analysis is performed to assess the mediating role of PR on the associations: PAT → (comment, endorse, and pass-on) and PCT → (comment, endorse, and pass-on). The output of the mediation analysis is shown in Table 6.

Predictive power – PLSPredict We apply the blindfolding procedure in SmartPLS with an omission distance of 8 to produce the Q-square values. Table 7 shows the results of the *PLSpredict* analysis. Upon examining the distribution of the error terms, we decided to use only the RMSE and not MAE. Sarstedt et al. (2021) recommended that MAE be used to assess the prediction error only when the distribution of the prediction errors is highly asymmetric. Otherwise, the RMSE should be sufficient. Generally, a model is considered to have a high predictive power if all indicators have low prediction errors. In contrast, when only a minority of the indicators have low predictive errors, the model is considered to have low predictive power, and it is considered to have a medium predictive power if most of the indicators have lower prediction errors. Since the Q-square values are all above zero, we conclude that the model has a predictive relevance.

Predictive accuracy – ML classification We further quantify the predictive accuracy of the latent predictive variables in predicting the intention to engage pre-purchase. To achieve this, the latent response variables were transformed into a binary form that allows testing the hypotheses in hand. The numerical threshold value that best classifies the response variable is specified by selecting the threshold of the best performing model (e.g., Sharkasi et al. 2015). we build six classification algorithms with tenfold cross-validation. To examine the performance of the classification models, we inspect the confusion matrix as in the accuracy level of the model and follow the rule of thumb in machine learning. Table 8 reports the performance metrics of the confusion matrix of the best performing classifier to test all paths of Model A. All accuracy, precision and recall scores are greater than 75%. The accuracy scores of the paths of this structural model range between 83.73 and 90.43%. All precision, recall, and F-measure values are above 0.75, which indicates a very good prediction ability of the model. Therefore, the results confirm the significance of PR and PAT and PCT in predicting the intention to comment, endorse and share pre-purchase.

Alternative models analysis Figure 2 illustrates the alternative models presented in some literature. The hypotheses of the alternative model A-i which hypothesize that PR affects PAT and PCT, respectively, are found significant with β = − 0.081, ρ= 0.045; and β = − 0.101, ρ= 0.043, respectively. Regarding out-of-sample *PLSPredict* output, the Q-square values are all above zero, moreover, the Q-square values resulting from the structured model are all lower than the linear model. Thus, the models have a predictive relevance. However, when it comes to predictive accuracy, all classifiers gave accuracy values below 60% (see Table 9), these scores are considered too low to produce reliable predictions.

Table 6 Results of the mediation analysis of PR in the pre-purchase intention to engage

Total effects		Direct effect		Indirect effect		
Coefficient	ρ-value	Coefficient	ρ-value	Coefficient	ρ-value	Bias Interval
(PATàcomment)		(PATàcomment)		(PAT → PR → comment)		
0.271	0.001	0.12	0.032	− 0.151	0.001	0.080–0.262
(PAT → endorse)		(PAT → endorse)		(PAT → PR → endorse)		
0.446	0.001	0.195	0.027	0.251	0.011	0.001–0.091
(PAT → pass-on)		PAT → pass-on)		(PAT → PR → pass-on)		
0.298	0.012	0.144	0.001	0.154	0.001	0.309–0.458
(PCT → comment)		(PCT → comment)		(PCT → PR → comment)		
0.344	0.344	0.234	0.001	− 0.11	0.001	0.026–0.083
(PCT → endorse)		(PCT → endorse)		(PCT → PR → endorse)		
0.243	0.026	0.135	0.001	0.108	0.021	0.318–0.447
(PCT → pass-on)		(PCT → pass-on)		(PCT → PR → pass-on)		
0.337	0.016	0.162	0.013	0.175	0.001	0.027–0.085

Bias Interval is [2.5–97.5%]

Table 7 PLSPredict results

The paths	Diff. (RMSE) LM − PLS	(LM − PLS)/ PLS %	PLS Q^2	LM Q^2
Pre-purchase I2E model				
Pre-purchase I2E (comment1)	0.005	0.54	0.122	0.107
Pre-purchase I2E (comment2)	0.016	2.19	0.053	0.017
Pre-purchase I2E (comment3)	0.011	1.42	0.086	0.073
Pre-purchase I2E (endorse1)	0.018	1.25	0.091	0.055
Pre-purchase I2E (endorse2)	0.021	1.55	0.083	0.047
Pre-purchase I2E (endorse3)	0.013	1.17	0.023	0.004
Pre-purchase I2E (pass-on1)	0.027	2.00	0.065	0.029
Pre-purchase I2E (pass-on2)	0.028	1.96	0.028	0.016
Pre-purchase I2E (pass-on3)	0.031	2.30	0.039	0.005
Satisfied post-purchase I2E model				
Sat. post-purchase I2E (comment1)	0.009	0.81	0.363	0.347
Sat. post-purchase I2E (comment2)	0.016	1.14	0.303	0.262
Sat. post-purchase I2E (endorse1)	0.018	1.14	0.114	0.094
Sat. post-purchase I2E (endorse2)	0.002	0.13	0.132	0.130
Sat. post-purchase I2E (endorse3)	0.101	6.68	0.327	0.227
Sat. post-purchase I2E (pass-on1)	0.029	1.99	0.239	0.209
Sat. post-purchase I2E (pass-on2)	0.024	1.54	0.138	0.110
Sat. post-purchase I2E (pass-on3)	0.000	0.00	0.136	0.136
Dissatisfied post-purchase I2E model				
DisSat. post-purchase I2E (comment1)	0.101	6.68	0.327	0.227
DisSat. post-purchase I2E (comment2)	0.022	1.90	0.373	0.348
DisSat. post-purchase I2E (pass-on1)	0.015	1.24	0.440	0.431
DisSat. post-purchase I2E (pass-on2)	0.101	6.68	0.327	0.227
DisSat. post-purchase I2E (pass-on3)	0.041	3.57	0.358	0.309

I2E Intention to engage, *Sat.* satisfied, *DisSat* dissatisfied

Table 8 Predictive accuracy scores of the classification models of pre-purchase intention to engage

#	Path	Classifier	TP rate	FP rate	Precision	Recall	F-measure	Accuracy
1	PAT → PR	J48	0.900	0.905	0.817	0.900	0.856	89.95%
2	PAT → comment	Logistic	0.890	0.861	0.839	0.890	0.859	89.00%
3	PAT → endorse	AdaBoostM1	0.900	0.860	0.853	0.900	0.865	89.95%
4	PAT → share	J48	0.895	0.905	0.817	0.895	0.854	89.47%
5	PCT → PR	Bayes Net	0.895	0.905	0.817	0.895	0.854	89.47%
6	PCT → comment	J48	0.904	0.725	0.880	0.904	0.885	90.43%
7	PCT → endorse	Bayes Net	0.876	0.886	0.783	0.876	0.826	87.56%
8	PCT → share	Logistic	0.876	0.886	0.783	0.876	0.826	87.56%
9	PR → comment	J48	0.880	0.886	0.783	0.880	0.829	88.04%
10	PR → endorse	AdaBoostM1	0.852	0.817	0.808	0.852	0.827	85.17%
11	PR → share	Bayes Net	0.876	0.886	0.783	0.876	0.826	87.56%
12	Structural system of equations	Comment	0.880	0.886	0.783	0.880	0.829	88.04%
13		Endorse	0.880	0.886	0.783	0.880	0.829	88.04%
14		Pass-on	0.880	0.886	0.783	0.880	0.829	88.04%

TP True positives, *FP* false positives, *PR* perceived risk, *PAT* perceived affective trust, *PCT* perceived cognitive trust, *I2E* intention to engage

Table 9 Predictive accuracy scores of the classification models of pre-purchase intention to engage for alternative model A-i

#	Path	Classifier	TP rate	FP rate	Precision	Recall	F-measure	Accuracy
1	PR → PAT	J48	0.598	0.61	0.544	0.598	0.557	59.81%
2	PAT → comment	Logistic	0.569	0.683	0.482	0.569	0.513	56.94%
3	PAT → endorse	Logistic	0.598	0.67	0.491	0.598	0.523	59.81%
4	PAT → share	Logistic	0.793	0.884	0.645	0.793	0.712	56.94%
5	PR → PCT	J48	0.761	0.746	0.665	0.761	0.709	58.85%
6	PCT → comment	AdaBoostM1	0.793	0.884	0.645	0.793	0.712	56.94%
7	PCT → endorse	AdaBoostM1	0.569	0.683	0.482	0.569	0.513	56.94%
8	PCT → share	J48	0.598	0.61	0.544	0.598	0.557	59.81%
9	PR → comment	J48	0.761	0.746	0.665	0.761	0.709	58.85%
10	PR → endorse	AdaBoostM1	0.598	0.67	0.491	0.598	0.523	59.81%
11	PR → share	Bayes Net	0.793	0.884	0.645	0.793	0.712	56.94%

Regarding the alternative model, A-ii, where PR has no association with PAT and PCT, the hypotheses of the effect of all the indicator variables on the pre-purchase intention to engage are found significant. Similarly, the *PLSPredict* output of the Q-square values are all above zero. However, the overall accuracy score of the model is found to be very low and amounts to 60%, with F-measure of 0.545 and recall and precision scores of 0.60 and 0.50, respectively. The TP and FP rates are both found to be 0.60.

Model B: Satisfied post-purchase intention to engage and the moderating effect of perceived risk

Model fit For Satisfied post-purchase intention to engage, the model's SRMR is 0.074 < 0.08. The model's NFI values for post-purchase comment, endorse, and pass-on are 0.957; 0.955; and 0.935 > 0.90, respectively. Thus, the model fits the data well. The R-squared values of all constructs are above 0.25 and reported in Table 5.

Hypotheses testing The findings of the satisfied post-purchase intention to engage model show that all the PAT and PCT hypotheses are accepted. As shown in Table 5, hypotheses, H2–a, -b, and -c, which predict that PAT positively affect the intention to comment, endorse, and share an FB advert when satisfied with its product/service. All coefficient of the effect of PAT on commenting, endorsing and sharing are significant by (β = 0.202, f-square = 0.249, ρ = 0.002), (β = 0.252, f-square = 0.243, ρ = 0.000), and (β = 0.275, f-square = 0.182, ρ = 0.005), respectively. Moreover, all the hypotheses of PCT are significant. Hypotheses, H5–a, -b, and -c, which predict that PCT positively affect the intention to comment on, endorse, and share a FB advert are all significant by (β = 0.122, f-square = 0.016, ρ = 0.052), (β = 0.159, f-square = 0.104, ρ = 0.027), and (β = 0.134, f-square = 0.210, ρ = 0.032), respectively.

Moderation analysis We use the product-indicator approach (Chin 1998; Chin et al. 2003) for moderation analysis because of its wide application on models with reflective observed variables. The moderation effect of PR on the association between PAT → satisfied post-purchase intention to engage (comment, endorse, and share) is examined through the following three main steps:

1. The dependent variables (intention to comment, endorse, and pass-on) are regressed on the independent variables (PAT and PCT) along with the moderator variable, PR. The R^2 values of this main effect model, reported in Table 10, indicate that the independent variables (PAT and PCT) and the moderator, PR, explain 28.1%, 28.3%, and 25.5% of the variance in the intention to comment, endorse, and pass-on when satisfied post-purchase, respectively.
2. The interaction term of the moderator variable, PR, and the independent variables, (PR × PAT) and (PR × PCT), are added to the main effect model. The R^2 values of the dependent variables, (comment, endorse, and pass-on), reported in Table 10, indicate that the model explains 49.4%, 45.1% and 40.1% of the variance in the intention to comment, endorse, and pass-on, when satisfied post-purchase, respectively.
3. Lastly, we compute the effect size, f^2, by subtracting the R^2 of the main effect model from the R^2 of the model with the insertion of the interaction effect and divide the outcome by (1 − R^2 of the main effect model). The f^2 values of the dependent variables (comment, endorse, and pass-on), reported in Table 10, are significant, ρ <0.001, and greater than 0.15 which indicates that the effect size is moderate (Cohen 1988).

The results confirm a direct link between PAT and PCT and satisfied post-purchase intention to engage (comment, endorse, and pass-on) and support the positive moderating effect of PR (measured on the pre-purchase stage) with a moderate effect size. The cut-off value of the t-value resulting from the bootstrapping technique is 1.645 (α =0.05)

Table 10 Moderation analysis output

#	Variables	Estimated β	SE	t-value	ρ-value
Satisfied post-purchase intention to engage					
1	PAT – comment	0.129	0.088	1.699	0.019
2	PAT – endorse	0.187	0.063	2.008	0.000
3	PAT – pass-on	0.409	0.072	3.820	0.021
4	PCT – comment	0.185	0.058	2.010	0.002
5	PCT – endorse	0.177	0.055	1.892	0.010
6	PCT – pass-on	0.277	0.043	2.985	0.010
7	PR – comment	0.119	0.022	1.698	0.000
8	PR – endorse	0.117	0.048	1.690	0.001
9	PR – pass-on	0.109	0.028	1.697	0.002
10	PAT × PR	0.213	0.058	2.988	0.002
11	PCT × PR	0.210	0.038	2.976	0.000
		Without interaction terms		With interaction terms	
		R^2		R^2	f^2
12	comment	0.281		0.494	0.296
13	endorse	0.283		0.451	0.234
14	pass-on	0.255		0.401	0.196
Dissatisfied post-purchase Intention to Engage					
1	PAT – comment	0.186	0.068	1.898	0.009
2	PAT – pass-on	0.185	0.056	1.895	0.024
3	PCT– comment	0.167	0.033	1.765	0.006
4	PCT – pass-on	0.150	0.025	1.695	0.019
5	PR – comment	0.125	0.078	1.697	0.000
6	PR – pass-on	0.113	0.078	1.698	0.001
7	PAT × PR	0.221	0.016	2.987	0.001
8	PCT × PR	0.212	0.023	2.966	0.000
		Without interaction terms		With interaction terms	
		R^2		R^2	f^2
9	R^2– comment	0.273		0.369	0.132
10	R^2– pass-on	0.261		0.288	0.037

and 2.33 ($\alpha = 0.01$). This means with high level of PAT and PCT; the moderator PR (measured in the pre-purchase stage) has a significant positive effect on the overall level of engagement when satisfied.

Predictive power As shown in Table 7, our results show that the Q-square values of the linear model (LM) are all lower than the corresponding values of the PLS-SEM model, and all Q-square values of the PLS-SEM model are greater than zero, this indicates an adequate predictive power of the PLS model.

Predictive accuracy: ML classification. We split the dataset into high vs. low PR and perform classification analysis. The results reported in Table 11 shows that the recall values of all classifiers are above 0.75. The classifiers' accuracy scores confirm the significance of PAT and PCT in predicting the intention to comment, endorse and share when satisfied post-purchase. The accuracy scores are above 0.60 which is a common minimum threshold to accept the prediction accuracy of a classifier.

Model C: Dissatisfied post-purchase intention to engage and the moderating effect of perceived risk

Model fit For dissatisfied post-purchase intention to engage, the model's SRMR value is $0.070 < 0.08$, and the model's NFI values are 0.910 and $0.945 > 0.90$, for dissatisfied post-purchase intention to comment, endorse, and pass-on, respectively. As reported in Table 5, the R-squared values are all above 0.25.

Hypotheses testing The findings of the dissatisfied post-purchase I2E model show that all the PCT and PAT hypotheses are accepted. As shown in Table 5, hypotheses, H3–a and –b, which predict that PAT positively affect the intention to comment on and share an FB advert promoting a product/service with which the participant had a dissatisfactory purchase experience, are all significant by ($\beta = 0.176$, f-square = 0.152, $\rho = 0.009$) and ($\beta = 0.175$, f-square = 0.206, $\rho = 0.024$), respectively.

Table 11 Predictive accuracy scores of the classification models of satisfied post-purchase intention to engage

#	Path	Classifier	TP rate	FP rate	Precision	Recall	F-measure	Accuracy
High perceived risk								
1	PAT → comment	J48	0.857	0.508	0.844	0.857	0.839	85.71%
2	PAT → endorse	Logistic	0.857	0.508	0.844	0.857	0.839	85.71%
3	PAT → share	J48	0.857	0.508	0.844	0.857	0.839	85.71%
4	PCT → comment	AdaBoostM1	0.843	0.570	0.824	0.843	0.818	84.29%
5	PCT → endorse	J48	0.857	0.508	0.844	0.857	0.839	85.71%
6	PCT → share	J48	0.814	0.814	0.500	0.814	0.619	81.43%
7	Structural system of equations	Comment	0.857	0.508	0.844	0.857	0.839	85.71%
8		Endorse	0.857	0.508	0.844	0.857	0.839	85.71%
9		Share	0.857	0.508	0.844	0.857	0.839	85.71%
Low perceived risk								
1	PAT → comment	Logistic	0.837	0.855	0.791	0.837	0.813	83.73%
2	PAT → endorse	Logistic	0.843	0.570	0.824	0.843	0.818	84.29%
3	PAT → share	J48	0.814	0.814	0.500	0.814	0.619	81.43%
4	PCT → comment	AdaBoostM1	0.857	0.508	0.844	0.857	0.839	85.71%
5	PCT → endorse	AdaBoostM1	0.814	0.814	0.500	0.814	0.619	81.43%
6	PCT → share	J48	0.876	0.886	0.783	0.876	0.826	87.56%
7	Structural system of equations	Comment	0.843	0.57	0.824	0.843	0.818	84.29%
8		Endorse	0.843	0.57	0.824	0.843	0.818	84.29%
9		Share	0.843	0.57	0.824	0.843	0.818	84.29%

TP True positives, *FP* false positives, *PR* perceived risk, *PAT* perceived affective trust, *PCT* perceived cognitive trust, I2E intention to engage

The hypotheses H6–a and –b which predicted that PCT positively affect the intention to provide a negative comment on a FB advert when dissatisfied or share a negative post on an FB advert are also significant by (β = 0.157, f-square = 0.216, ρ = 0.006) and (β = 0.140, f-square = 0.120, ρ = 0.019), respectively.

Moderation analysis The R^2 values of the intention to comment and pass-on when dissatisfied post-purchase in the main effect model (R^2 values: 0.273 and 0.261, respectively) compared to the R^2 values of the model with the moderation interaction (R^2 values: 0.369 and 0.288, respectively). The results reported in Table 10 confirm a direct link between PAT and PCT and dissatisfied post-purchase intention to engage (comment, and pass-on). The results indicate that PR has a weak effect size for the intention to comment ($f^2 = 0.132$) and even weaker for the intention to share pass-on ($f^2 = 0.037$).

Predictive power As shown in Table 7, our results show that the Q-square values of the linear model (LM) are all lower than the corresponding values of the PLS-SEM model, and all Q-square values of the PLS-SEM model are greater than zero, this indicates an adequate predictive power of the PLS model.

Predictive accuracy: ML classification Table 12 confirms that PAT and PCT significantly predict the intention to comment and share when dissatisfied post-purchase.

Further analysis

In this study, we use *PLSPredict* and classification-based ML algorithms out-of-sample prediction approaches to confirm the ability of the structural models to form proper managerial implications (Sarstedt and Danks 2022). Due to a conflicting finding in *PLSPredict* and ML classification of the alternative models proposed in the literature to study pre-purchase intention to engage, we confirm the consistency of the proposed classification-based ML algorithms with other in-sample model's statistics by conducting basic consistency analysis with ± 1 tolerance. We compare the in-sample model statistics as in the hypotheses' average coefficients and R-squared values of the dependent variables of the model with its corresponding accuracy scores of the classification-based ML algorithms. We compute the average of the coefficients of the model then rank the average values to compare them with the ranking of the corresponding accuracy scores. We also compare the rank of the constructs' R-squared values and the corresponding accuracy scores in Table 13.

Even though the R-squared value does not tell us whether the model is good or not, it is a good estimate that explains the variance in the dependent variable explained by the independent variables. For example, an R-squared of 0.283 for the intention to comment pre-purchase means that, the PR and PCT explain 28.3% of the variance in the

Table 12 Predictive accuracy scores of the classification models of dissatisfied post-purchase intention to engage

		Classifier	TP rate	FP rate	Precision	Recall	F-measure	Accuracy
High perceived risk								
1	PAT → comment	J48	0.614	0.424	0.612	0.614	0.613	61.43%
2	PAT → share	Logistic	0.614	0.424	0.612	0.614	0.613	61.43%
3	PCT → comment	AdaBoostM1	0.614	0.424	0.612	0.614	0.613	61.43%
4	PCT → share	AdaBoostM1	0.614	0.424	0.612	0.614	0.613	61.43%
5	Structural system of equations	Comment	0.614	0.424	0.612	0.614	0.613	61.43%
6		Share	0.614	0.424	0.612	0.614	0.613	61.43%
Low perceived risk								
1	PAT → comment	J48	0.809	0.820	0.668	0.809	0.732	80.86%
2	PAT → share	Logistic	0.876	0.886	0.783	0.876	0.826	87.56%
3	PCT → comment	J48	0.876	0.886	0.783	0.876	0.826	87.56%
4	PCT → share	AdaBoostM1	0.871	0.887	0.782	0.871	0.824	87.08%
5	Structural system of equations	Comment	0.814	0.814	0.500	0.814	0.619	81.43%
6		Share	0.814	0.814	0.500	0.814	0.619	81.43%

TP True positives, *FP* false positives, *PR* perceived risk, *PAT* perceived affective trust, *PCT* perceived cognitive trust, *I2E* intention to engage

Table 13 Rankings of the models' accuracy scores, R-square, and average coefficients

The model	Avg. coefficients	R-square	Rankings		
			Model's coefficients	Construct R-square	Classification ML
Pre-purchase the intention to engage					
Intention to comment	0.2090	0.283	2	3	1
Intention to endorse	0.2063	0.285	3	2	2
Intention to pass-on	0.3267	0.257	1	7	3
Satisfied post-purchase intention to engage					
Intention to comment	0.1620	0.286	7	1	4
Intention to endorse	0.2055	0.259	4	6	5
Intention to pass-on	0.2045	0.260	5	5	6
Dissatisfied post-purchase intention to engage					
Intention to comment	0.1665	0.270	6	4	8
Intention to pass-on	0.1575	0.252	8	8	7

intention to comment. Moreover, the coefficients of the exogenous variables in the PLS-SEM represent a linear regression system of equations whereby the higher the coefficients, the stronger the direct effect. Thus, we took the average of the absolute values of the coefficients and not the sum of the coefficients for comparative analysis. The rankings of the average coefficient scores and the R-squared values are considered for comparative analysis due to their relation to the significance of the hypotheses as in-sample statistics.

Discussion and implications

Key findings and discussion

This paper investigates and empirically tests the effect of PR and trust (defined in this study by PAT and PCT and measured in the pre-purchase state) on the intention to engage with an FB advert. Findings indicate that all independent variables, PR and PAT and PCT, play a role in affecting the intention to engage pre- and post-purchase. The mediation analysis confirms the significant positive mediation effect of PR on the association between perceived trust (PAT and PCT) and the intention to comment pre-purchase. This implies that, the relationship with a product advertised on FB will be surrounded by much risk at an early stage, and this would make interested prospects more likely to communicate their inquiries by commenting to solicit responses to mitigate uncertainties. The findings also confirm the negative mediation effect of PR on the association between perceived trust (PAT and PCT) and the intention to endorse and share pre-purchase. This implies that, initial PAT and PCT pre-purchase mitigate PR and thus prospects are more likely to endorse and share.

Research suggests that perceived trust is built over time (Koufaris and Hampton-Sosa 2004), therefore, our hypotheses testing support that 'initial' PAT and PCT pre-purchase negatively affect PR. This result agrees with a number of research studies (e.g., Ventre and Kolbe 2020; Marriott and Williams 2018). Table 8 shows that the hypothesized structural model of the mediation effect of PR on the association of perceived trust (PAT and PCT) and the pre-purchase intention to comment, endorse and pass-on has the highest accuracy value among all models which amounts to 88.04% with F-measure of 0.829. In line with this result, Ventre and Kolbe (2020) and Marriott and Williams (2018) support the mediation effect of PR over the association between trust and behavioral intentions.

Regarding the alternative models of the pre-purchase intention to engage in Fig. 2, researchers could rely on the accuracy scores resulting from classification-based ML algorithms to assess PLS models. The accuracy scores of the classification-based ML algorithms for the paths of the alternative models were less than 60% which is too low to be considered for reliable prediction analysis (see Table 9). Therefore, the findings of the ML classification analysis of the alternative models conflict with the results of: (i) the hypotheses significance testing, and (ii) out-of-sample metrics– obtained from the *PLSPredict* analysis package –. To obtain a clarity on the conflicting hypothesized structural models—present in the literature—we also conduct comparative consistency analysis. In Table 13, the comparisons between the ranking of the classification-based ML accuracy scores and the models' PLS-SEM analysis metrics (average coefficients and the constructs' R-squared values) show 50% match in the dissatisfied post-purchase intention to engage. The comparisons in the pre-purchase and satisfied post-purchase intention to engage show 66.6% in match consistency within a $\pm$ one unit tolerance. The results of the consistency analysis confirm the usability of the classification-based ML algorithms to quantify the model's predictive accuracy which produces results with about 50–67% consistency with the conventional PLS-SEM model's metrics.

Regarding the intention to comment, endorse and pass-on post-purchase when satisfied, PAT and PCT are found to have a positive effect on the intention to engage with a positive moderation effect of PR. The classification-based ML model of the moderation effect of high-level PR on the association between perceived trust (PAT and PCT) and satisfied post-purchase intention to engage had an accuracy and F-measure values of 85.71% and 0.839, respectively. These values are close to those obtained from the low-level PR sample, with accuracy score of 84.29% and F-measure of 0.818.

This positive moderating effect of PR could be explained by the expectation confirmation theory which explains the effect of PR on the intention to engage in relation to satisfaction (Oliver 1980). The expectation confirmation theory posits that satisfaction is directly affected by the disconfirmation of beliefs (as in the disconfirmation of uncertainty or PR). This implies that prospects' expectations drop with higher pre-purchase PR, and despite the high-risk, highly interested prospects who take the risk and commit to a purchase, are more likely to engage when satisfied with the purchase through an FB advert (due to the positive disconfirmation of PR). Furthermore, previous research confirms a possible association between PR and happiness (Ayadi 2010). Risk-taking and the decision to engage in uncertain activities such as risky financial choices (Chen et al. 2020) or unsafe extreme sports (Bikker and Fink 2022) are also explained by the positive association of pre-purchase PR and the consumer's well-being through inducing positive emotions. Moreover, the sharing of emotions with strangers as in engaging with FB adverts is found to be satisfying (López-López et al. 2014). Thus, we could understand the positive moderating effect of PR on the association between trust and the satisfied post-purchase intention to engage by considering PR as a vector of happiness.

Regarding the moderation effect of PR and the intention to comment or pass-on when dissatisfied, the findings show a positive significant effect. Regarding the classification-based ML model, the accuracy score of the structural model of the low-level PR is 81.43% and the F-measure is 0.619, while the high-level PR sample dataset has a lower accuracy and F-measure scores of 61.43% and 0.613, respectively. The findings imply that dissatisfied consumers are more likely to engage when their initial PR before placing an order was at the low end, thus, feeling disappointment for not meeting their expectations (due to the negative disconfirmation of PR).

Theoretical contributions

This study makes several contributions to the literature on social commerce engagement. First, the study contributes to the literature on consumer engagement in that it models the role of perceived risk and trust as the main facilitators of engagement. The current study shows that PR plays a mediation effect in the pre-purchase stage and a moderation effect in the post-purchase stage.

The prevailing view is that perceived risk has a negative effect on desired consumer behavior as in the intention to purchase and engage (Ao et al. 2023). The literature has also provided inconsistent findings regarding the relationship with other constructs including perceived trust (see Appendix I). Prior studies have examined individual decisions on whether to engage pre-purchase, but not in post-purchase (see Appendix I). By extending the research to test varying PLS structural configurations or outlines of the relationship between perceived risk and trust, particularly in the pre-purchase stage, we uncovered the positive effect of perceived risk on the intention to comment (eWoM). When one is motivated to alleviate uncertainty by gathering information, s/he comments on the FB advert and anticipate a response. This study proposes that the accuracy scores of the classification-based ML algorithms can be used to confirm the significance of the structural model and quantifies its accuracy, especially, in the case of the conflicting alternative models as in the relationship of PR and trust (PAT and PCT) and their effect on behavioral intentions.

Second, the current study adds to our understanding about individual's engagement decisions post-purchase. The study reveals the stark difference between the model's accuracy scores in the dissatisfied post-purchase intention to engage vs. the satisfied. In doing so, this study questions the popular view that focuses on examining pre-purchase intention models and ignores investigating post-purchase. When modeling the moderating effect in post-purchase, we recommend splitting the data into two subsamples based on low vs. high levels of PR. Then, apply classification-based ML algorithms on each subsample to produce the corresponding accuracy scores. The results show that, in both cases of satisfied vs. dissatisfied post-purchase intention to engage, the accuracy scores resulting from the low-level PR were lower compared to the accuracy scores resulting from the sample of high-level PR in the dissatisfied post-purchase intention to engage. The findings imply that dissatisfied consumers are more engaging when their initial PR before placing an order was on the low side rather than the high. We could thus gather that risk averse customers are more likely to engage with an FB advert when dissatisfied.

Managerial and practical implications

The findings revealed some important implications for FB advertisers and uncovered a significant contribution to the body of knowledge in several different ways. First, the knowledge of the mediating effect of PR on the association between perceived trust (PAT and PCT) and the pre-purchase intention to comment calls for the importance of social listening to detect prospects' inquiries and swiftly respond to prospects' comments pre-purchase. While marketing managers strive to communicate a low risk directly or indirectly through various marketing activities, PR is an inevitable issue when acquiring new customers (Alrawad et al. 2023a, b). It is important for marketing experts to control the level of PR by possibly withholding some product-related information to induce customers to gather information. Research suggests that, in the information gathering stage, customers tend to alleviate uncertainty by inquiring in the comments section of the FB advert. To take advantage of the positive effect of PR in the pre-purchase stage, implementing a promptly responsive communication strategies, especially at the early stages of the marketing campaign, could help prospects receive answers to their inquiries and thus set their product expectations right. At the same time, it helps enhance the engagement score for SEO.

Second, regarding the satisfied post-purchase intention to engage, each positive comment serves as a building block, contributing to the overall perception of a brand (Jain et al. 2023). Such feedback help improve products and services or co-create innovative offerings (Soloaga et al. 2023). Positive testimonials are crucial to build credibility, they also serve as a social proof (Naeem 2021). Moreover, engagement improves search engine optimization SEO and thus its ranking on the search engine results page (Leung and Chan 2021). One of the challenges remains is the ability to strike a balance between negative and positive comments and their effect on all engagement actions pre- and post-purchase.

Third, the moderating effect of PR on the association between perceived trust (PAT and PCT) and the dissatisfied post-purchase intention to engage (comment and pass-on) has important practical implications. Customers who have trusted in the brand are considered more valuable due to the positive effect of trust on loyalty (Abid et al. 2023). Research suggest that brand-trusted and loyal customers are more likely to write a positive eWoM after resolving their dissatisfaction (Wang and McCarthy 2023). This relationship could be explained by understanding the drivers of the tendency to share negative experiences on social media (Bigné et al. 2023). Some research suggests a positive effect of a certain type of PR, as in social risk, and engaging in negative e-WoM on social media (Nuzula and Wahyudi 2022). Social listening tools coupled with Omni-channel implementation help detect negative eWoM that originate from disappointed but trusting customers. An ample investment in such tools and a customer relationship management (CRM) system help marketers promptly identify and act upon valuable customers. These practices can turn a negative review into a positive one and further enhance the loyalty of customers and the engagement score of the FB advert.

Limitations and future research directions

Although this research provides new insights, it has limitations and raises several new research questions. First, the study's participants are mainly from Southeast Asia with little representations of other regions. Moreover, the sample size could have been larger for generalization purposes. It is recommended to replicate this study in other countries and cultures for confirmation or comparison analysis. It is also recommended to investigate the variables of this study on other popular social media platforms, e.g., Instagram.

Although PR and PAT and PCT explained a substantial amount of variance in the intention to engage, other possible factors can be added to the research model (e.g., perceived behavioral control and subjective norms). The propensity to take risk (Alrawad et al. 2023a, b) and also the propensity to trust (Wang and McCarthy 2023) could be interesting variables to consider for future research. In addition, cultural related constructs could have an influence on communication style (Wang and Liu 2019; Zhai et al. 2023) and on the intention to engage. A more complex relationships as in the interaction of network size and tie strength may be considered as antecedents of sharing (Kim and Koh 2023) and thus could be considered for future research. It is interesting to investigate whether the intention to engage pre-purchase affects the intention to engage post-purchase. Recent research suggests that the effect of trust on impulsive consumer behavior is bi-dimensional and more complex than its effect on planned buying (Attah et al. 2023). Therefore, future research should examine the applicability of our findings in impulse engagement under varying cultural contexts in the pre- and post-purchase stages of the customers' journey.

Appendix I: The relationship between perceived risk and trust in the customer behavior literature

Context	Authors	Relationships perspectives	Phase in customer's Journey	Constructs of the study
Online purchase intention	Munikrishnan et al. (2023)	Mediation effect of trust on the perception of risk and online purchase intention	Pre-purchase	Financial risk; product risk; time risk; psychological risk; Trust
Intention to use	Alrawad et al. (2023a, b)	Mediating effect of trust on association of perceived risk and the intention to use	Pre-purchase	Institutional-based trust; characteristics-based trust; process-based trust
Intention to use and attitude toward use	Almaiah et al. (2023)	Perceived risk affects perceived trust	Pre-purchase	Perceived risk; perceived trust; perceived security; perceived ease of use; perceived usefulness; social influencer; service quality

Context	Authors	Relationships perspectives	Phase in customer's Journey	Constructs of the study
FinTech Use	Amnas et al. (2023)	Perceived risk affects trust	Pre-purchase	Performance expectancy; social influence; effort expectancy; hedonic motivation; price value; habit; facilitating condition; perceived risk; trust; reputation; service quality; regulatory support
Online purchase intention and actual online purchase	Sari et al. (2020)	Perceived risk affects trust	Pre-purchase and actual purchase	eWoM; reputation; security practice; privacy concern; trust; perceived risk
Online purchase intention	Kindangen et al. (2021)	Mediating effect of trust on the association of perceived risk and the intention to use	Pre-purchase	Perceived risk; trust
Tourists' trust	Abror et al. (2022)	Perceived risk affects perceived trust	Pre-purchase	perceived risk; trust; perceived value; religiosity
Intention to use e-government; future intention to use	Ejdys et al. (2019)	Perceived risk affects perceived trust. Mediating role of perceived trust in e-government	Pre-purchase	Perceived risk; perceived security level; trust in e-government; future intention to use

Context	Authors	Relationships perspectives	Phase in customer's Journey	Constructs of the study
Purchase intention at times of food crisis	Hoque and Alam (2018)	Mediating effect of trust on the association of perceived risk and the intention to purchase	Pre-purchase	Perceived risk; perceived knowledge; attitude; trust in information sources; trust in product (liquid milk)
Online grocery purchase intention	Habib and Hamadneh (2021)	No relationship between perceived risk and trust	Pre-purchase	Social influence; effort expectancy; performance; facilitation; hedonic motivation; customer technology acceptance; trust; perceived risk
Behavioral intention to use mobile payment	Widyanto et al. (2022)	Mediating effect of perceived risk on the association of perceived trust and the behavioral intention		social influence; facilitating conditions; perceived security, performance expectancy; trust; perceived risk
eWoM and purchase intention	Amarullah et al. (2022)	No relationship between perceived risk and trust	Pre-purchase	eWoM credibility; trust; perceived risk; online shopping experience; purchase intention
Brand loyalty	Hasan et al. (2021)	No relationship between perceived risk and trust	Pre-purchase	Trust; interaction; perceived risk; novelty value

Context	Authors	Relationships perspectives	Phase in customer's Journey	Constructs of the study
Purchase intention and online reviews	Ventre and Kolbe (2020)	Trust affects perceived risk. Mediation effect of trust	Pre-purchase	Perceived usefulness of online reviews; trust; perceived risk
Mobile shopping	Marriott and Williams (2018)	Trust affects risk. Mediation effect of trust	Pre-purchase	Risk; trust
Behavioral intention; usage behavior of digital wallet	Khan and Abideen (2023)	Moderating effect of trust on perceived risk and usage behavior of digital wallet	Actual behavior	Perceived usefulness; perceived ease of use; perceived compatibility; perceived social influencer; perceived service quality; perceived trust; perceived risk
Behavioral intention	Esawe (2022)	Trust affects risk	Pre-purchase	Trust; risk; performance expectancy; effort expectancy; social influence; facilitating conditions
Purchase intention from online marketplace	Aslami et al. (2022)	Perceived risk affects perceived trust. Mediation of trust	Pre-purchase	Perceived ease of use; perceived risk; e-WoM; trust; purchase intention
Purchase intention online	Qalati et al. (2021)	Moderating effect of perceived risk on the association of trust and purchase intention	Pre-purchase	Perceived risk; trust; perceived service quality; perceived website quality; perceived reputation

Appendix II: Perceived risk and customer engagement literature

Perceived risk type	Authors	Relationship with trust and engagement	Summary
privacy risk	Jozani et al. (2022)	Social media apps and cognitive trust	Discussed privacy concerns and benefits of engagement with social media-enabled apps
Privacy risk	Alam et al. (2023)	Airline industry websites and affective trust	Advertising attractiveness and perceived privacy concerns both significantly affect engagement with pro-environmental campaigns
Privacy risk	Yan et al. (2023)	Subscription vs. purchase-based mobile social apps; perceived privacy risk and affective trust	It is important to investigate privacy and product information risks since they deter prospective customers from buying frequently and spending a significant amount of money
Information risk	Cadwalladr and Graham-Harrison (2018)	Perceived risk and cognitive trust when engaging with mobile applications	Narrate the Cambridge Analytics scandal with Facebook's "platform policy" where both public and private data of millions of FB users were unknowingly harvested by a mobile app

Perceived risk type	Authors	Relationship with trust and engagement	Summary
Information risk	Wang and Liu (2019)	Perceived risks when posting about organizations on social media and trust	Studied motives for sharing eWOM and established eight new typologies for such motives
Product or authenticity risk	Hohlbaum et al. (2019)	Perceived product risk and cognitive trust	The study explores if virtual reality (VR) vs. a 2D display of an online shop reduces the perceived product risk
Product and delivery risk	Sawang et al. (2023)	Perceived product and delivery risk and affective trust	Investigated perceived risk and emotional wellbeing of consumers
Product risk	Barta et al. (2023)	Perceived product risk and pre-purchase expectations and engagement	They argue that reducing risk and the comfort it brings generates decision confidence and satisfaction with the shopping experience. This satisfaction will generate engagement toward the online shop platform
Product return risk	Salem and Alanadoly (2024)	Perceived product's return risk and engagement	Return policy positively moderates the relationship between customer engagement and customer citizenship behavior in the omnichannel fashion retail context
Temporal and delivery risk	Asanprakit and Limna (2023)	Temporal risk and affective trust	Temporal risk can affect consumer confidence when making repeat purchases from a particular retailer or brand
Temporal risk	Sawang et al. (2023)	Temporal risk and affective trust	"If a purchase requires an unreasonable amount of time and effort, customers hesitate to buy from that source, this can further reduce consumer loyalty and trust levels"
Temporal risk	Foroudi et al. (2021)	Temporal risk and affective trust	Perceived risk moderates the relationship between adoptive belief and anticipated emotions which affect future desire to possibly engage

Data availability The study participants have not given written permission to share their data publicly.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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