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Challenging the Mediator: How Users' Goals Influence Perceived System Usability, Outcomes Satisfaction, and Platform Usage in Digital Commerce

Haslinda Musa[1], Umi Kartini Rashid[2], Mohd Syafiq Md Taib[1], Nur Zafirah A Khadar[3]

[1]Universiti Teknikal Malaysia Melaka, Malaysia

[2] Universiti Tun Hussein Onn, Johor, Malaysia

[3] ERADA Solutions Sdn Bhd. Ayer Keroh Melaka, Malaysia

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ABSTRACT

The purpose of this research is to examine the effects of the core design characteristics including loading time, the attributes of electronic commerce, the dynamics of pricing strategies, and the usability of the website, on satisfaction and popularity of the platform and the moderating role of device type. A mediated-moderated model was tested using information gathered from 346 online shoppers in Malaysia using Partial Least Squares Structural Equation Modeling (PLS-SEM). Loading time and usability have a significant impact to satisfaction for usability user satisfaction has a negative relationship, indicating possible impacts of usability complexity. Interestingly, dynamic pricing and e-commerce features were not found to enhance satisfaction perceptibly, and satisfaction itself did not mediate the relationship between design features and stage popularity. Instead, user friendliness and e-commerce capability influenced popularity because of usability within online services, and it is obvious in case of popularity. In addition, device type had a moderating effect on the link between loading time and satisfaction which confirms the popularity of mobile sensitivity in usability research. Although discriminant validity is questioned the model shows very high predictive power ($R^2 > 0.97$), providing novel insights into direct-only pathways in platform evaluation. The study contributes to the digital commerce literature by questioning the mediation role of user satisfaction and suggesting the contextual relevance of device-led usability expectations. Theoretical and design strategy considerations for mobile-first markets are considered.

Keywords: e-commerce usability, platform popularity, user satisfaction, mobile shopping, PLS-SEM

INTRODUCTION

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it. The rapid expansion of e-commerce sites has revolutionized worldwide consumer behavior and digital retail ecosystems. In Southeast Asia, and Malaysia specifically, the advent of mobile-first commerce has changed the way consumers interact with digital ecosystems like Shopee, Lazada and Amazon. Existing studies focused on the determinants of e-commerce adoption by focusing on technological and marketing antecedents, and mechanisms by which platform features can affect user satisfaction and user-perceived platform popularity have not been examined in detail, especially in mobile-first markets.

Problem Statement

Despite the maturation of online retail systems, consumer retention and sustained platform engagement continue to challenge even the most dominant e-commerce providers. The success of an e-commerce platform is not merely a function of its features or price competitiveness but increasingly hinges on how users perceive their interaction experiences including responsiveness, usability, trust, and convenience. As platforms become

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more technologically sophisticated, users develop elevated expectations for seamless interaction, particularly on mobile devices. However, scholarly understanding of which platform attributes truly drive satisfaction and popularity remains fragmented, often limited to studies focused on adoption intent or transactional behavior, rather than broader platform loyalty or reputation effects.

A common theoretical assumption in e-commerce literature is that user satisfaction mediates the relationship between platform features and platform success outcomes such as loyalty, revisit intention, or popularity. Models such as the Technology Acceptance Model (TAM) and Expectation Confirmation Theory (ECT) have long positioned satisfaction as a pivotal construct linking system qualities to behavioral outcomes (Bhattacherjee, 2001). Yet, recent empirical evidence has begun to question the centrality of satisfaction, particularly in environments where performance factors such as loading time, dynamic pricing, and usability may exert direct influence on consumer perception and behavior (Lemon & Verhoef, 2016; Wang et al., 2022).

In addition, while usability is typically assumed to enhance satisfaction, some emerging studies suggest that excessive feature complexity or cognitive load may negatively affect satisfaction, especially for mobile users who interact with platforms in time-constrained or fragmented contexts (Tarute et al., 2017). Furthermore, the role of device types of an increasingly relevant moderator in the omnichannel era remains under-theorized in structural models of platform evaluation.

This problem exists within a broader academic gap in the post-adoption phase of e-commerce interaction. While early models have thoroughly examined adoption drivers, fewer studies have focused on how users evaluate platforms after adoption, and which platform elements predict perceived popularity or reputational success. As the field moves beyond clickstream analysis and transaction-level data, scholars have called for richer models that capture experiential constructs and test complex interrelationships among usability, performance, and attitudinal outcomes (Venkatesh et al., 2016; Grewal et al., 2021).

This study narrows its focus to the Malaysian e-commerce landscape, using Shopee and Lazada as contextual anchors due to their market dominance and mobile-first infrastructure. It investigates four core platform characteristics loading time, features of e-commerce, dynamic pricing strategies, and website usability and their effects on user satisfaction and perceived platform popularity. The model includes user satisfaction as a mediating variable, and device type as a moderator, using a robust PLS-SEM approach to test direct, indirect, and interaction effects.

The theoretical problem the potential overreliance on satisfaction as a mediating construct is directly addressed through the empirical testing of both direct and mediated paths. Additionally, the contextual problem the lack of clarity around how platform design features impact popularity in mobile-first contexts is reflected in the inclusion of device type as a moderator. This study builds a structural model that allows these questions to be tested simultaneously, thereby providing clarity on whether user satisfaction retains its mediating power, or whether design attributes have independent influence on how platforms are perceived.

By empirically challenging traditional mediation assumptions, this study expects to clarify the role of user satisfaction in e-commerce evaluation models. It seeks to provide evidence on whether usability, pricing, and features affect platform success directly or indirectly, and how these relationships are influenced by the user's device context. The findings have implications not only for academic theory such as refining post-adoption models but also for designers and strategists aiming to optimize digital platform experiences, especially in mobile-first environments.

Research Objectives

In response to these gaps, the study is designed to achieve the following objectives:

1) To examine the direct effects of platform attributes (loading time, features, pricing, and usability) on user satisfaction.
2) To assess whether user satisfaction mediates the relationship between platform attributes and perceived platform popularity.

3) To evaluate the direct influence of user satisfaction on platform popularity.
4) To determine the moderating role of device type on the relationship between loading time and user satisfaction.
5) To validate a structural model that explains the antecedents of platform popularity in a mobile-first e-commerce context.

Research Gap and Significant

Despite the extensive research on e-commerce adoption and consumer behavior, there remain critical gaps in understanding how specific platform characteristics influence post-adoption outcomes such as user satisfaction and perceived platform popularity particularly in mobile-first digital environments. While traditional models such as the Technology Acceptance Model (TAM) and Expectation-Confirmation Theory (ECT) emphasize user satisfaction as a mediating construct (Bhattacherjee, 2001; Davis, 1989), emerging studies suggest that this assumption may be overstated in today's complex e-commerce ecosystems (Lemon & Verhoef, 2016; Venkatesh et al., 2016).

Recent research has pointed out the lack of clarity in the mediating role of satisfaction, especially when users interact with platforms that are functionally rich but cognitively demanding (Tarute, Nikou, & Gatautis, 2017; Grewal, Ailawadi, Harlam, Kopalle, & Raju, 2021). For instance, website usability has long been associated with improved satisfaction and loyalty (Cyr, 2008), yet more recent findings show that usability enhancements if perceived as complex or unintuitive can paradoxically reduce satisfaction due to cognitive overload (Wang, Xu, & Gao, 2022). This contradiction highlights a need to reassess how usability, features, and performance metrics influence satisfaction and reputation in modern digital platforms.

Additionally, platform popularity, a construct often assumed to emerge from satisfaction and engagement, is under-theorized in e-commerce literature. Most models focus on behavioral outcomes like purchase intention or loyalty, without accounting for reputational or communal evaluations of platforms (Pentina, Zhang, & Basmanova, 2013). The mechanisms through which consumers perceive a platform as "popular" remain largely untested, particularly in relation to observable platform characteristics such as loading speed, pricing dynamics, and usability.

Furthermore, device type, while recognized as a key contextual variable in human-computer interaction (HCI), remains underexplored as a moderator in structural models of digital commerce. With increasing dependence on mobile devices in Southeast Asia (Google, Temasek, & Bain, 2022), understanding how device context influences satisfaction formation is essential for platform designers and digital strategists. Yet, most existing models treat technology use as homogeneous, ignoring the profound impact that mobile device constraints (e.g., screen size, latency, bandwidth) have on user experience.

Taken together, these gaps underscore the need for an integrated model that not only tests the traditional mediating role of satisfaction but also accounts for direct effects of platform characteristics and the moderating impact of device type. This research addresses these critical gaps by constructing and validating a PLS-SEM model that incorporates both mediated and moderated pathways, thus contributing to a more nuanced understanding of platform evaluation in post-adoption contexts.

From a practical standpoint, this study is significant for e-commerce managers, UX designers, and digital strategists. It provides evidence on which design elements truly matter to users, whether satisfaction is still the central metric, and how mobile users may perceive performance and usability differently. These insights are invaluable for optimizing digital retail platforms in competitive, rapidly evolving markets like Southeast Asia.

LITERATURE REVIEW

The dynamic and competitive nature of the e-commerce industry demands that digital platforms offer not only transactional efficiency but also highly optimized user experiences. Contemporary research in e-commerce and information systems has begun shifting from adoption-focused models to investigations into post-adoption user behavior, satisfaction, and platform perception. This study contributes to that shift by investigating how key platform characteristics loading time difference, features of e-commerce, dynamic pricing strategies, and website usability affect user satisfaction and, subsequently, platform popularity, with device type introduced as a moderator. Each construct is reviewed below considering relevant literature.

Loading Time Difference

Despite the maturation of online retail systems, consumer Website loading speed has long been recognized as a core component of system quality (DeLone & McLean, 2003). Fast-loading platforms enhance the perception of technological efficiency and reliability, both of which are critical to forming positive user experiences. In e-commerce, delays as minimal as a few seconds have been shown to reduce customer satisfaction and increase bounce rates (Park & Kim, 2003). Wang et al. (2022) found that interface load time significantly affects mobile users' satisfaction, emphasizing the urgency of system responsiveness in mobile contexts. As users increasingly access e-commerce platforms through smartphones with variable bandwidth conditions, the difference in loading times becomes a salient determinant of platform evaluation. Hence, this study posits that loading time directly influences user satisfaction and indirectly affects platform popularity.

Features of E-Commerce

Platform features refer to the functionalities and tools available to users, such as wish lists, multiple payment options, tracking systems, reviews, and advanced filtering. These features contribute to perceived usefulness, a central element in the Technology Acceptance Model (Davis, 1989), and later refined models like UTAUT (Venkatesh et al., 2016). Kim and Stoel (2004) found that well-integrated features improve perceived enjoyment and satisfaction in apparel shopping platforms. More recent work by Liu, Feng, and Hu (2020) confirmed that feature richness is positively associated with post-adoption satisfaction and perceived platform value. However, overloading users with excessive or poorly integrated features may backfire, leading to usability concerns. This dual potential makes it critical to test the feature satisfaction popularity linkage.

Dynamic Pricing Strategies

Platform features refer to the functionalities and tools Dynamic pricing the use of algorithms to alter prices in real time based on demand, competition, or user behavior is now common in digital commerce. While some users appreciate the perception of "smart deals," others may react negatively to perceived unfairness or manipulation (Grewal et al., 2021). Price fairness has been shown to moderate the impact of dynamic pricing on trust and satisfaction (Xia et al., 2004). Moreover, research by Chen and Xie (2008) revealed that pricing transparency and perceived fairness directly influence satisfaction and behavioral loyalty. In Southeast Asian markets, where price sensitivity is high, the psychological response to dynamic pricing may differ from Western contexts, necessitating localized empirical testing.

Website Usability

Usability encompasses ease of navigation, clarity of layout, and responsiveness of user interfaces (Nielsen, 2000). In e-commerce, it is one of the most consistent predictors of user satisfaction and loyalty (Cyr, 2008; Rose et al., 2012). However, recent studies show that the relationship may not always be linear. Tarute et al. (2017) found that overengineered or complex interfaces, especially on mobile devices, can negatively affect satisfaction, indicating a potential threshold effect. This is particularly relevant in high-context, mobile-first markets, where usability must balance feature richness with cognitive simplicity. This study explores whether the traditionally assumed positive relationship between usability and satisfaction still holds true.

User Satisfaction

User satisfaction is defined as the positive emotional response resulting from the fulfillment of user expectations (Bhattacherjee, 2001). It is central to the Expectation Confirmation Theory (ECT) and has been widely used as a predictor of continuance intention, loyalty, and advocacy in digital platforms. However, emerging models suggest that satisfaction is not always a necessary mediator; instead, design quality or usability may directly shape user evaluations (Lemon & Verhoef, 2016). This raises the need to empirically test whether satisfaction still acts as a mediating mechanism between platform characteristics and outcomes such as popularity.

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Platform Popularity

Platform popularity, though less frequently modeled than adoption or loyalty, is an important reputational construct that reflects perceived dominance, preference, and user volume. It is shaped by social proof, platform visibility, and collective user perception (Pentina et al., 2013). While popularity can be influenced by marketing and network effects, platform usability and performance may also directly shape how users perceive popularity, independent of personal satisfaction. This distinction is critical because it suggests a dual path model: one through personal satisfaction and another through direct evaluation of features.

Device Type (Moderator)

Device type specifically mobile vs. desktop access has emerged as a critical moderator in digital behavior studies. Mobile users often interact with platforms under different cognitive, temporal, and ergonomic constraints than desktop users (Lee, Kim, & Sundar, 2015). As such, the importance of usability, responsiveness, and performance is amplified in mobile contexts. Wang et al. (2022) argue that mobile device users are more sensitive to interface loading and system delays, making it essential to test whether device type moderates the relationship between platform features and satisfaction. This study explores whether loading time exerts a stronger effect on satisfaction for mobile users, in line with HCI and UX theory.

The literature reveals strong theoretical and empirical support for each construct individually. However, the combined model proposed in this study integrating usability, pricing, system performance, and platform features into a moderated-mediation framework has not been extensively tested, especially in mobile-first, emerging market contexts. There is a clear research opportunity to explore whether user satisfaction retains its central mediating role or whether observable platform traits drive popularity perceptions directly. This study addresses that gap through a structural model tested with empirical data from Malaysian e-commerce users.

Development of the Conceptual Framework

The preceding literature review highlights the theoretical and empirical foundations for examining the relationships between platform characteristics, user satisfaction, and perceived platform popularity within e-commerce environments. Across studies, constructs such as loading time, usability, feature richness, and pricing strategy consistently emerge as influential factors in shaping consumer experiences (Cyr, 2008; Liu et al., 2020; Wang et al., 2022). However, their precise roles especially in terms of direct versus mediated effects are still subject to debate, particularly within mobile-first digital ecosystems such as those in Southeast Asia.

Notably, while traditional models such as TAM (Davis, 1989) and ECT (Bhattacherjee, 2001) place user satisfaction at the center of behavioral outcomes, recent scholarship suggests that certain platform attributes may influence evaluative outcomes directly, bypassing emotional or cognitive intermediaries (Lemon & Verhoef, 2016; Venkatesh et al., 2016). For example, in performance-critical tasks like mobile shopping, users may judge a platform’s popularity not necessarily through reflective satisfaction but through observable and tangible design elements like responsiveness, clarity, or feature utility (Rose et al., 2012; Grewal et al., 2021).

Building on this foundation, the present study positions user satisfaction as a potential mediator between four

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key platform attributes loading time difference, features of e-commerce, dynamic pricing strategies, and website usability and perceived platform popularity. While past models have conceptualized these relationships, empirical testing that simultaneously integrates all four antecedents and both mediated and direct paths remains scarce. Moreover, by introducing device type as a moderating variable, this study accounts for the differential expectations and constraints encountered by mobile versus desktop users, a dimension often overlooked in prior models.

In sum, the proposed conceptual framework reflects both theoretical continuity and empirical refinement. It tests:

1) Whether user satisfaction mediates the effects of design and performance attributes on platform popularity.
2) Whether device type moderates the impact of loading time on satisfaction.
3) And whether some platform attributes exert direct effects on popularity, independent of user satisfaction.

The framework presented (e.g. Fig.1) integrates these theoretical relationships into a mediated-moderated structural model that guides the subsequent hypotheses and analysis.

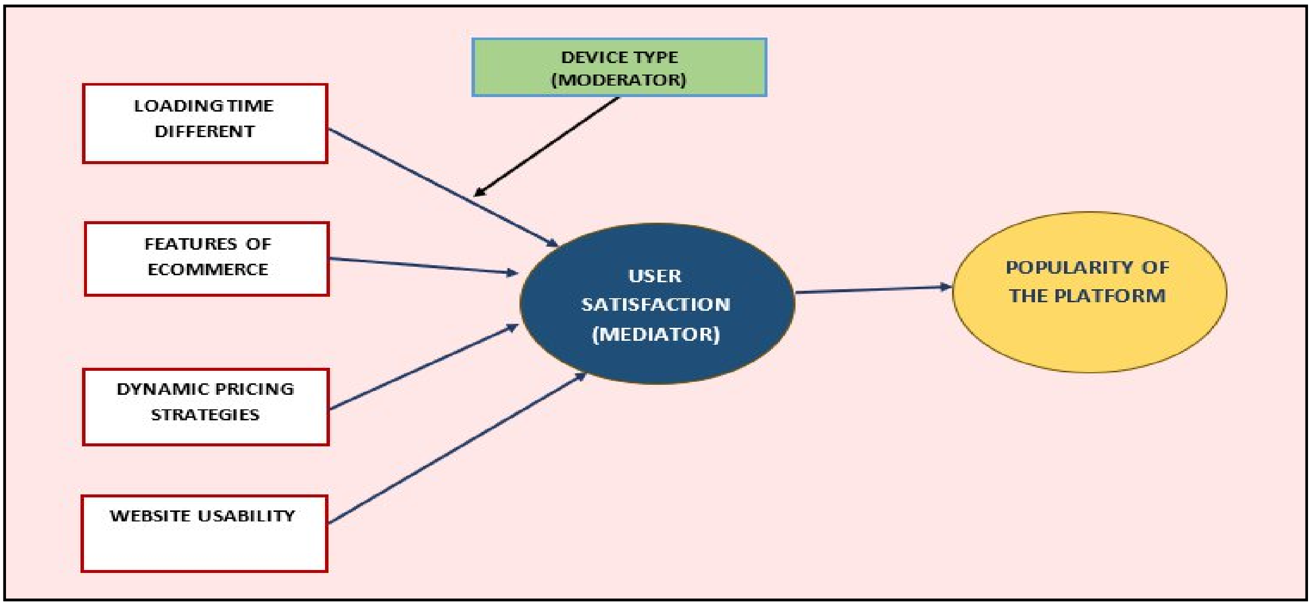

Fig 1. Conceptual Framework

User Satisfaction

User satisfaction is defined as the positive emotional response resulting from the fulfillment of user expectations (Bhattacherjee, 2001). It is central to the Expectation Confirmation Theory (ECT) and has been widely used as a predictor of continuance intention, loyalty, and advocacy in digital platforms. However, emerging models suggest that satisfaction is not always a necessary mediator; instead, design quality or usability may directly shape user evaluations (Lemon & Verhoef, 2016). This raises the need to empirically test whether satisfaction still acts as a mediating mechanism between platform characteristics and outcomes such as popularity.

Hypothesis Development

Drawing on the literature and theoretical underpinnings discussed, this study formulates a series of hypotheses to examine the relationships between platform characteristics, user satisfaction, and perceived platform popularity, with a focus on mediating and moderating effects.

Direct Effects

H1: Loading time difference has a significant effect on user satisfaction.

Page responsiveness and system speed are foundational elements of user experience. Research suggests that delays in loading time negatively impact satisfaction, particularly for mobile users who expect instant interactions (Wang et al., 2022). Thus, faster-loading platforms are expected to yield higher satisfaction.

H2: Features of e-commerce platforms have a positive impact on user satisfaction.

Feature-rich platforms offering functionalities like advanced search, order tracking, and personalized recommendations contribute to user-perceived value and utility (Kim & Stoel, 2004). These features, when well-integrated, are expected to enhance user satisfaction by meeting diverse needs.

H3: Dynamic pricing strategies significantly affect user satisfaction.

While dynamic pricing can increase perceived deal value, it may also raise concerns about fairness and consistency (Grewal et al., 2021). As such, the study hypothesizes that dynamic pricing if perceived as fair can enhance satisfaction, but empirical testing is needed to confirm its directionality.

H4: Website usability positively influences user satisfaction.

Usability, encompassing interface clarity, navigation ease, and responsiveness, directly contributes to a positive user experience (Cyr, 2008). Platforms with higher usability are expected to yield greater satisfaction as users navigate and complete tasks more efficiently.

H5: User satisfaction positively predicts the perceived popularity of e-commerce platforms.

User satisfaction, as an evaluative response, contributes to downstream perceptions such as loyalty, advocacy, and platform reputation (Bhattacherjee, 2001). Satisfied users are more likely to view the platform as popular, influential, or preferable among alternatives.

Mediating Effects of User Satisfaction

The mediating role of user satisfaction is well supported in models such as Expectation Confirmation Theory and post-adoption technology use. This study extends that logic to test whether platform design features influence perceived popularity indirectly via user satisfaction.

H6: User satisfaction mediates the relationship between loading time difference and e-commerce platform popularity.

A faster loading time may not only improve the user experience but also enhance satisfaction, which in turn influences platform popularity perception.

H7: User satisfaction mediates the relationship between e-commerce features and platform popularity.

The availability of diverse and user-centric features is expected to increase satisfaction, which may translate into greater perceptions of platform popularity.

H8: User satisfaction mediates the relationship between dynamic pricing and platform popularity.

If users perceive dynamic pricing as advantageous or fair, it may increase satisfaction, which then positively affects how popular the platform is perceived to be.

H9: User satisfaction mediates the relationship between website usability and platform popularity.

Higher usability enhances satisfaction, which may serve as a channel through which users develop a favorable perception of the platform's popularity and influence.

Moderating Effect of Device Type

Device type introduces an important contextual dimension. Mobile users often experience platforms differently due to screen size, data load speed, and context of use. This study introduces device type as a moderator to test whether mobile users respond more strongly to performance cues.

H10: Device type moderates the relationship between loading time difference and user satisfaction, such that the relationship is stronger for mobile users.

Given the limitations and expectations associated with mobile devices, loading time is hypothesized to have a stronger effect on satisfaction for mobile users than for desktop users.

METHODOLOGY

This study adopts a quantitative, cross-sectional design aimed at empirically examining the interplay between e-commerce platform characteristics, user satisfaction, and perceived platform popularity, incorporating the moderating effect of device type. The research is grounded in an explanatory paradigm and is designed to test both direct and mediated relationships within a complex model. A Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was selected due to its robustness in handling models with latent constructs, reflective indicators, and both mediation and moderation structures. Furthermore, PLS-SEM is recognized for its predictive orientation and suitability for theory development, particularly in studies with relatively modest sample sizes and complex path models (Hair et al., 2021; Sarstedt et al., 2022).

The measurement instrument was developed through careful adaptation of previously validated scales from the information systems and digital marketing literature. All variables were operationalized using five-point Likert scales ranging from "strongly disagree" to "strongly agree." The constructs measured included loading time difference, features of e-commerce, dynamic pricing strategies, website usability, user satisfaction, device type, and platform popularity. Each construct was assessed using six items drawn and adapted from foundational and recent works. For instance, user satisfaction items were adapted from Bhattacherjee's (2001) expectation-confirmation model, while website usability was guided by Cyr (2008) and usability heuristics grounded in Nielsen's dimensions. The construct of dynamic pricing drew on the work of Grewal et al. (2021), and the operationalization of platform popularity was newly developed, reflecting consumer perception of reputation, visibility, and frequency of platform usage. Face and content validity were assured through iterative reviews by both academic experts in information systems and industry practitioners in the e-commerce domain.

The data collection employed purposive sampling to target Malaysian consumers with recent online shopping experience, thereby ensuring relevance and contextual accuracy. The final sample comprised 346 valid responses, a size deemed adequate for PLS-SEM analysis considering model complexity. Respondents were recruited via online channels and completed a structured questionnaire administered through Google Forms. The Malaysian context was chosen strategically due to the country's burgeoning mobile-first e-commerce ecosystem, where platforms like Shopee dominate usage among young, tech-savvy consumers (Google, Temasek, & Bain, 2022). To mitigate common method bias, several procedural remedies were implemented. These included randomization of question items, anonymity assurances, and the inclusion of reverse-coded items, in line with recommendations by Podsakoff et al. (2003).

The data analysis followed the two-step PLS-SEM approach. First, the measurement model was evaluated to confirm the reliability and validity of the latent constructs. Indicator reliability was confirmed as all factor loadings exceeded the recommended threshold of 0.70. Internal consistency reliability was evidenced by high Cronbach's alpha and Composite Reliability (CR) values, both above 0.90 for all constructs. Convergent validity was established as the Average Variance Extracted (AVE) values for each construct surpassed the benchmark of 0.50. However, discriminant validity presented challenges. While the Fornell–Larcker criterion was met in most cases, the HTMT (Heterotrait–Monotrait) ratio revealed values exceeding the acceptable threshold of 0.90, indicating conceptual overlap, particularly between user satisfaction and usability-related constructs. This issue, while not uncommon in experience-based models, suggests that future refinements in construct dimensionality may be necessary (Sarstedt et al., 2022).

Subsequently, the structural model was assessed to evaluate the hypothesized relationships among constructs. The significance of path coefficients was tested using bootstrapping with 5,000 resamples, and multicollinearity was examined via Variance Inflation Factor (VIF) values, all of which remained below the critical threshold of 10. The model's explanatory power was demonstrated by the R^2 values of 0.970 for user satisfaction and 0.985 for platform popularity, indicating strong variance explanation. Mediation and moderation analyses were conducted through indirect path assessments and interaction term modeling, respectively. Predictive relevance was confirmed through Stone-Geisser's Q^2 values, which were well above zero, supporting the model's out-of-sample predictive power (Shmueli et al., 2019). Additionally, f^2 effect sizes were reported to assess the practical significance of predictors, with website usability and device type showing notably large effects on platform popularity and user satisfaction, respectively.

Ethical considerations were adhered to throughout the research process. Participants were informed about the voluntary nature of the study, assured of confidentiality, and provided consent prior to data collection. The study followed the ethical standards set by the Declaration of Helsinki and was approved by the institutional ethics committee of the authors' affiliated university.

In summary, the methodological framework of this study integrates robust measurement practices, a theoretically grounded model structure, and advanced analytical techniques appropriate for modeling complex relationships in e-commerce platform evaluation. The use of PLS-SEM not only facilitates the testing of both mediating and moderating effects but also aligns with contemporary standards in digital commerce and information systems research.

RESULTS

Demographic Profile of Respondents

Table I Profile Of Respondents

Profile	**Category**	**Number of Respondents**	**% of Respondents**
Gender	Male	158	45.7%
	Female	188	54.3%
Age Group	18–24	186	53.8%
	25–30	40	11.6%
	Above 30	120	34.7%
Income Level	Below RM1,000	14	4.0%
	RM1,000–3,000	117	33.8%
	RM3,001–5,000	175	50.6%
	Above RM5,000	40	11.6%
Online Shopping Frequency	Once a month or less	88	25.4%
	2–3 times a month	113	32.7%
	Weekly	79	22.8%

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	Almost daily	66	19.1%
Most Used Platform	Amazon	18	5.2%
	Shopee	239	69.1%
	Lazada	59	17.1%
	Others	30	8.7%

The research administered questionnaires that have been expanded on by other researchers, to 346 respondents spanning ages, levels of education, statuses in tertiary, and other backgrounds as indicated in Table I. 54.3% of the participants were females, while the remaining 45.7% were males. Young adults made up most of the respondents with 53.8% aged between 18 24 years, 11.6% aged between 25 30 years and 34.7% above 30 years. Among the respondents, 50.6% income received between RM3,001-5,000, 33.8% between RM1,000-3,000 and 4% received less than RM1,000 (see Table 1).

As for online shopping, 32.7% of the respondents shopped online 2-3 times a month, followed by 25.4% that shopped online once a month or less. Some 22.8% shopped on a weekly basis and another 19.1% of the more frequent shoppers shopped almost daily. Results show that Shopee was clearly the most used e-commerce platform, with 69.1% of respondents who chose the ecommerce platform most widely used in that section, followed by Lazada (17.1%), by other platforms (8.7%) and by Amazon (5.2%). The demographics indicate that the sample is Malaysian consumers who are young to middle aged, with moderate income level, who regularly shop online and use Shopee.

Descriptive Statistics for Study Variables

Table Ii Descriptive Statistics

(N, MINIMUM, MAXIMUM, MEAN, STANDARD DEVIATION)

Variable	**N**	**Min**	**Max**	**Mean**	**SD**
Loading Time Difference	346	1.17	5.00	4.4355	0.78493
Features of E-Commerce	346	1.00	5.00	4.4364	0.76432
Dynamic Pricing Strategies	346	1.00	5.00	4.5535	0.82578
Website Usability	346	1.00	5.00	4.5414	0.80621
User Satisfaction	346	1.00	5.00	4.3743	0.79704
Device Type	346	1.00	5.00	4.4417	0.80391
Platform Popularity	346	1.17	5.00	4.5255	0.81920
Valid N (listwise)	346				

Descriptive statistics for all study variables are presented in Table II. It is found in the results that respondents generally have high ratings for all these variables scored from 4.37 to 4.55 out of 5.00. The stratgy with maximum mean score (4.55) is Dynamic Pricing Strategies followed by Website Usability (4.54) and Platform Popularity (4.53). These high scores indicate that the respondents agreed strongly with statements associated with these constructs. However, the mean score of User Satisfaction (4.37) had the lowest score among the results with general agreement.

It was found that the standard deviations of all variables were low, ranging from 0.76 and 0.82; hence participants were consistent in responses to all items. E-Commerce featured with Loading Time Difference and Features had equal mean value i.e., 4.44 and 4.44 respectively, hence, indicating the equal importance to users. There is also another indicator in Device Type rated high (mean = 4.44), which implies that respondents have a positive opinion on the importance of mobile devices in online shopping. The results point out that pricing strategies and website usability aspects are highly important to Malaysian e-commerce users, and these are ranked equally important to the other aspects of online shopping.

Evaluation of Measurement Model

PLS-SEM analysis (e.g. Fig. 2) was used to evaluate the measurement model. It is the necessary first step prior to evaluating structural model, in such a way that it verifies whether the constructs are valid and reliable. The analysis was geared towards confirming the relationships between the indicators and their respective latent variables to confirm that the measurement instruments measure what they aim to measure.

Table Iii Construct Reliability, Validity, And Collinearity Test Result

Latent Variable	Indicators	Factor Loadings	(VIF)	(α)	(CR)	(AVE)
Dynamic Pricing Strategies	DPS1	0.944	8.401	0.961	0.969	0.838
	DPS2	0.915	4.720			
	DPS3	0.883	3.752			
	DPS4	0.923	9.299			
	DPS5	0.902	5.808			
	DPS6	0.924	9.763			
Device Type	DT1	0.839	5.048	0.944	0.955	0.781
	DT2	0.892	3.381			
	DT3	0.894	4.098			
	DT4	0.897	4.865			
	DT5	0.900	6.557			
	DT6	0.878	3.368			
Features of E-Commerce	FE1	0.845	4.162	0.932	0.947	0.749
	FE2	0.762	2.612			
	FE3	0.872	4.717			
	FE4	0.893	5.703			
	FE5	0.912	4.618			
	FE6	0.901	4.526			
Loading Time Difference	LTD1	0.877	3.376	0.939	0.952	0.768
	LTD2	0.827	3.571			
	LTD3	0.874	3.633			
	LTD4	0.860	5.775			

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	LTD5	0.903	6.323			
	LTD6	0.914	4.477			
Website Usability	WU1	0.905	4.278	0.950	0.960	0.801
	WU2	0.892	3.528			
	WU3	0.892	3.570			
	WU4	0.922	4.943			
	WU5	0.883	3.495			
	WU6	0.876	3.377			
User Satisfaction	US1	0.923	20.536	0.940	0.953	0.773
	US2	0.846	4.019			
	US3	0.769	2.629			
	US4	0.933	21.779			
	US5	0.905	4.329			
	US6	0.888	4.000			
Platform Popularity	PP1	0.895	3.787	0.954	0.963	0.815
	PP2	0.893	3.606			
	PP3	0.924	5.454			
	PP4	0.878	3.537			
	PP5	0.957	8.692			
	PP6	0.866	2.968			

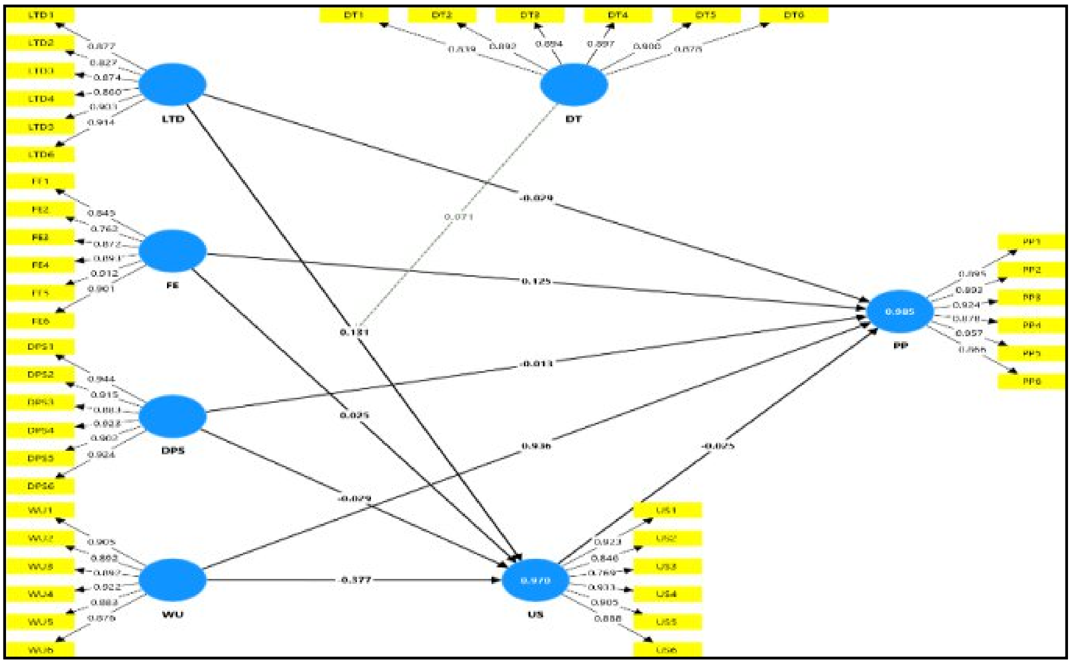

Fig 2. PLS-SEM factor loadings, path coefficients, and R2 values

The results of the assessment of the measurement model are presented in Table III following factor loadings, collinearity statistics and reliability and validity measures. All the indicators gave factor loadings well above the recommended threshold value that is 0.70 and the corresponding values are 0.957, 0.886, 0.762, 0.850. This shows that the relationships between each indicator and its corresponding construct are very strong. PP5 indicator was having the highest loading (0.957) whereas the lowest loading was observed in the case of FE2 indicator (0.762). The loadings of these indicators demonstrate high loadings, indicating that the indicators represent the constructs under which these indicators are found.

To detect multicollinearity problems, collinearity statistics, i.e. Variance Inflation Factor (VIF) were examined. All the VIF values were less than the critical threshold of 10 and most of them were in the range 3 - 6. Finally, if the highest VIF value was 21.779 for one of the User Satisfaction indicators, US4, it may be indicative of a potential collinearity problem. Thus, most of the indicators presented acceptable VIF values and, hence, multicollinearity did not seem to be a widespread phenomenon in the measurement model.

There were excellent results on reliability assessment across all constructs. Internal consistency of each of these constructs showed very high Cronbach's alpha values, 0.932–0.961. In like manner, composite reliability (CR) values were very good as they displayed values of 0.947 – 0.969, which is above the recommended threshold of 0.70. Such high reliability scores indicate that indicators for each construct are tightly linked and consistently monitoring the same concept.

Average Variance Extracted (AVE) values were assessed to check for Convergent validity. The AVE of all the constructs exceeded the recommended threshold of 0.50, with figures being 0.749 to 0.838. Dynamic Pricing Strategies have the highest AVE (0.838) while Features of ECommerce are the lowest (0.749). These results indicate strong support for the convergent validity for each construct; that is each construct explains a relatively high percent of the variance in its indicators.

Table Iv Discriminant Validity (Latent Variable Correlations And √Ave)

	DPS	DT	FE	LTD	PP	US	WU
DPS	**0.916**						
DT	0.960	**0.884**					
FE	0.981	0.966	**0.866**				
LTD	0.976	0.960	0.980	**0.876**			
PP	0.964	0.964	0.968	0.963	**0.902**		
US	0.944	0.981	0.951	0.950	0.941	**0.879**	
WU	0.969	0.974	0.971	0.969	0.992	0.949	**0.895**

The discriminant validity was however assessed. As a result of the square roots of AVE values (diagonal elements) and constructs' correlations (shown in Table IV), this table was constructed. The correlations between constructs were very high, many of which were over the square roots of AVE and were above 0.95 in most cases. This indicates discriminant validity issues of some constructs, i.e. there may be insufficient difference between some constructs and the others.

Table V Htmt (Heterotrait–Monotrait Ratio)

	DPS	DT	FE	LTD	PP	US	WU
DT	1.008						

FE	1.035	1.029					
LTD	1.026	1.019	1.046				
PP	1.006	1.016	1.027	1.017			
US	0.993	1.039	1.017	1.011	0.994		
WU	1.014	1.028	1.032	1.026	1.041	1.004	

The concern was further examined in Table V, using the Heterotrait-Monotrait (HTMT) ratio (HTMT ratio or HTMT) showed HTMT values of larger than 1.0, above the recommended threshold based 0.90.

Although the discriminant validity concerns dominate the results of the analysis, the measurement model performed very well in terms of indicator reliability, internal consistency and convergent validity. All the factor loadings, composite reliability, and AVE values met the recommended thresholds indicating that all constructs were well measured by their indicators. These discriminant validity issues do, however, preclude using the measurement data for proceeding with the structural model assessment, while the high quality of measurement does permit such an assessment (Hair et al., 2021). The measurement instruments could be refined for future research through deterring between the similar concepts in the e commerce environment.

Assessment of Structural Model

The measurement model was further confirmed of reliability and validity and subsequently the structural model was tested for the hypothesized relationship between constructs. The bootstrapping results are presented as shown (e.g. Fig. 3) to determine significance of path coefficients. In this assessment, direct effects, indirect effects, explanatory power of the model and predictive relevance were analyzed.

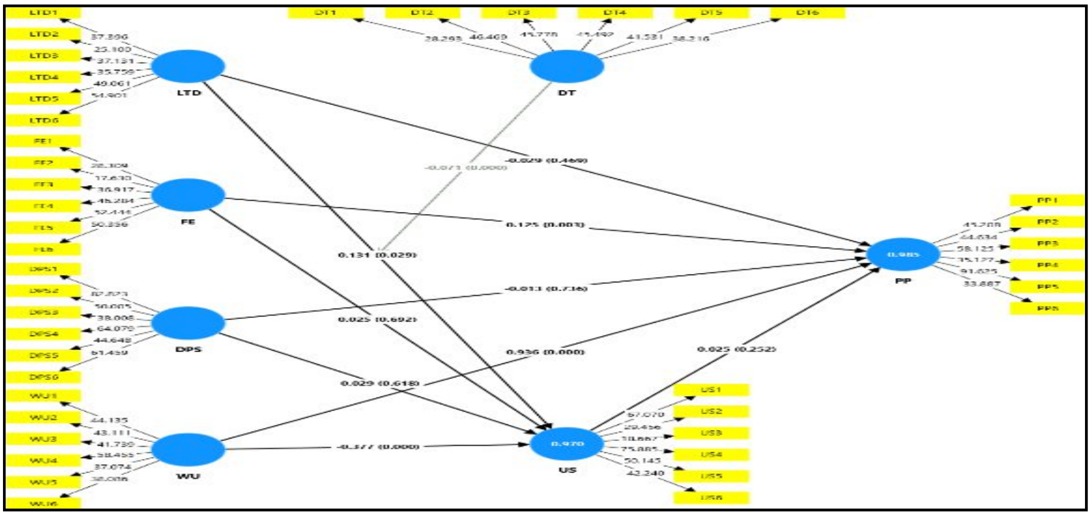

Fig 3. Bootstrapping Result

Table Vi Path Analysis Result: Direct Effects

Hypothesis	Path	Path Coefficient	t	p	Remark
H1	LTD → US	0.131	2.185	0.029	Accepted
H2	FE → US	0.025	0.396	0.692	Rejected
H3	DPS → US	-0.029	0.499	0.618	Rejected

H4	WU → US	-0.377	7.209	0.000	Accepted
H5	US → PP	-0.025	1.147	0.252	Rejected
H6	LTD → PP	-0.029	0.724	0.469	Rejected
H7	FE → PP	0.125	2.925	0.003	Accepted
H8	DPS → PP	-0.013	0.337	0.736	Rejected
H9	WU → PP	0.936	29.628	0.000	Accepted
H10	DT × LTD → US	-0.071	5.481	0.000	Accepted

Table VI shows the path analysis results of the direct effects. Only four out of the ten hypothesized relationships were statistically significant and hence accepted. Hypothesis 1 is supported by path coefficient of 0.131 ($t = 2.185$; $p = 0.029$) between Loading Time Difference (LTD) and User Satisfaction (US). Hypothesis 4 was also supported wherein Website Usability (WU) had a significant negative effect on User Satisfaction with a path coefficient of -0.377 ($t = 7.209$, $p < 0.001$) with the direction being opposite than what the one expected. Finally, Features of E-Commerce (FE) had positive significant effect on Platform Popularity (PP) with path coefficient of 0.125 ($t = 2.925$, $p = 0.003$) indicating support of Hypothesis 7. A strong, positive effect also exists between Website Usability and Platform Popularity with a path coefficient of 0.936 ($t = 29.628$, $p < .001$) and supports Hypothesis 9. Furthermore, the effect of interaction term Device Type × Loading Time Difference on User Satisfaction (path coefficient = -0.071, $t = 5.481$, $p < 0.001$), accredits to Hypothesis 10 related to the moderating effect of Device Type.

The data did not support the other hypothesized relationships. The use of User Satisfaction in Dynamic Pricing Strategies and Features of E-Commerce had no significant influence on the User Satisfaction ($p = 0.692$; $p = 0.618$, respectively). Platform Popularity could not be significantly predicted by User Satisfaction ($p = 0.252$). However, neither Loading Time Difference nor Dynamic Pricing Strategies had a significant effect on Direct Effect to Platform Popularity ($p = 0.469$ and $p = 0.736$, respectively).

Table 7 Path Analysis Result: Total Effects

Path	**t**	**p**	**Remark**
LTD → PP	0.812	0.417	Not Significant
FE → PP	2.890	0.004	Significant
DPS → PP	0.315	0.753	Not Significant
WU → PP	28.629	0.000	Significant
US → PP	1.147	0.252	Not Significant
DT → US	22.542	0.000	Significant
DT → PP	1.140	0.254	Not Significant
DT × LTD → PP	1.149	0.251	Not Significant

The analysis for total effects (both direct and indirect effects together) is presented in Table VII. The results showed that Features of E-Commerce ($t = 2.890$, $p = 0.004$) and Website Usability ($t = 28.629$, $p < 0.001$) had

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total effects on Platform Popularity. A significant total effect was observed on User Satisfaction (t = 22.542, p < 0.001) but not on Platform Popularity (t = 1.140, p = 0.254) by the Device Type. From this, it can be inferred that it is the device type that decides user experience and not platform popularity, which is quite the opposite emotion that was expected.

Table Viii Path Analysis Result: Total Indirect Effects

Path	t	p	Remark
LTD → US → PP	0.956	0.339	Insignificant effect
FE → US → PP	0.292	0.771	Insignificant effect
DPS → US → PP	0.369	0.712	Insignificant effect
WU → US → PP	1.129	0.259	Insignificant effect
DT × LTD → US → PP	1.149	0.251	Insignificant effect
DT → US → PP	1.140	0.254	Insignificant effect

As shown in Table VIII, the mediation analysis result shows that there was no significant mediating effect of User Satisfaction on the relationship between the independent variables and Platform Popularity. In all, p-values of all the indirect effects though User Satisfaction were greater than 0.05. However, this indicates that the factors affect Platform Popularity directly instead of through the route of User Satisfaction.

Table Ix R^2 And R^2 Adjusted Results

Latent Variable	R^2	R^2 Adjusted
US (User Satisfaction)	0.970	0.969
PP (Platform Popularity)	0.985	0.984

R^2 values of the model's explanatory power are presented in Table IX. The R^2 values for both User Satisfaction (R^2 =0.970) as well as Platform Popularity (R^2 = 0.985) are found to be very high. These values imply that model accounts for 97% of the explained variance in both User Satisfaction and in Platform Popularity. Similarly, high adjusted R^2 (0.969 and 0.984 respectively) showed that the model has a good explanatory power even with the number of predictors accounted for (Hair et al., 2021).

Table X F^2 Values

	US	PP
LTD	0.014	0.001
FE	0.001	0.017
DPS	0.001	0.000
WU	0.160	1.529
DT	2.285	0.001
DT × LTD	0.051	0.000

Table X presents f^2 to gauge the practical significance of each predictor. User Satisfaction varied the most based on Device Type ($f^2 = 2.285$): large practical impact. Platform Popularity was very much affected ($f^2 = 1.529$) by Website Usability. In some cases, statistical significance was not accompanied by a small or negligible effect size, meaning such predictors would likely have only small or negligible practical significance.

Table Xi Q^2 Values

Construct	Q^2
US	0.737
PP	0.795

Note: Q^2 values > 0 indicate predictive relevance. Q^2 values > 0 indicate predictive relevance.

As the final point, Q^2 values in Table XI are presented to confirm the predictive relevance of the model. The Q^2 values of User Satisfaction ($Q^2 = 0.737$) and Platform Popularity ($Q^2 = 0.795$) were found to be substantially above zero, hence proving the model's good predictive relevance. These results confirm that the model is not only capable of explaining the variance in the dependent variables but also has good predictive capability to new observations (Sarstedt et al., 2019).

CONCLUSION

This study offers a critical re-examination of user satisfaction’s mediating role in e-commerce platform evaluation, grounded in empirical data from a mobile-dominant Southeast Asian context. While conventional theory posits satisfaction as a central determinant of perceived platform success, our results suggest that observable design traits such as usability and feature richness directly influence platform popularity, bypassing affective mediators.

The unexpected negative relationship between website usability and satisfaction invites further inquiry into usability complexity and expectation disconfirmation, especially in mobile environments. Moreover, the lack of significant influence from dynamic pricing strategies challenges the notion that flexible pricing alone drives user approval highlighting the increasing emphasis on seamless, intuitive experiences.

The moderation effect of device type affirms the growing need for mobile-optimized performance. As mobile users become more dominant, their expectations for speed and ease-of-use demand special attention in design strategy.

The study’s strong explanatory power ($R^2 = 0.970$ for user satisfaction and 0.985 for platform popularity) reinforces the structural validity of the model, but also cautions against construct overlap, as evidenced by discriminant validity concerns. Future studies should refine measurement tools, explore trust and engagement as alternative mediators, and validate these relationships across diverse digital markets.

Ultimately, this research contributes to rethinking digital platform evaluations, proposing that in saturated, high-functionality environments, interface cues and user context (e.g., device type) may be stronger determinants of perceived platform success than satisfaction alone.

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