Impact of Website Stimuli on Online Impulse Buying: A Quantitative Analysis

S. W. Phoong[1,*] and G. S. Hoo[2]

[1]Department of Decision Science, Faculty of Business and Economics, Universiti Malaya, Kuala Lumpur, Malaysia
[2]Faculty of Business and Economics, Universiti Malaya, Kuala Lumpur, Malaysia
Email: phoongsw@um.edu.my (S.W.P.); 17217475@siswa.um.edu.my (G.S.H.)
[*]Corresponding author

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***Abstract*—Understanding the factors that influence consumers to buy impulsively in an online context has become increasingly important to businesses nowadays in order to help them stay competitive in the intensively competitive e-commerce market. Though existing literature has demonstrated how a website can improve the shopping experience and influence online shoppers to buy impulsively, the focus is more on design and quality dimensions such as visual appeal, website navigability, ease of use, etc. A more detailed analysis of how the advanced technology-supported website stimuli like recommender system, information search, customer services, and privacy & data security influence the consumer shopping experience and impulse buying behavior is still needed. Based on a Stimulus-Organism-Response model's conceptual framework and 403 valid respondents collected via an online questionnaire, this study aims to identify and explore the influence of advanced technology-supported website stimuli on customer satisfaction and online impulse buying behavior in the Malaysian context. The results showed that the recommender system, information search, and customer service had a significant influence on customer satisfaction, and the latter significantly impacted online impulse buying behavior.**

***Keywords*—customer satisfaction, online impulse buying, website stimuli**

I. Introduction

The advent of technology has changed the way people shop. Besides conventional in-store shopping, people nowadays can also shop and buy online. In 2021, 2.14 billion people were shopping online, a significant 62.1% increase compared to 1.32 billion in 2014 [1]. This strong growth of digital buyers has also boosted retail e-commerce revenue, recording a significant increase of 266.1% from USD1.32 trillion in 2014 to USD4.89 trillion in 2021 [1]. The growth in online buying is also driven by the rapid adoption of smartphones and mobile devices and the popularity of the internet. The large internet user population of 4.9 billion in 2021 indicates that nearly two-thirds of the world's population is now online [2].

More businesses are going online as a result of the shift in consumer buying habits and to survive the unprecedented COVID-19 pandemic [3]. Antwi [4] also revealed that the increasing number of e-retailers might be due to the similarity or high similarity of the products offered by these online merchants. A survey in 2020 showed that 40% of e-commerce companies in North America and Europe found their market competition very tough [1]. Moreover, the competition is not only from their peers in the online context but also from the recently reopened brick-and-mortar stores [3], as most countries are now entering the endemic stage and have loosened most of the COVID-19 measures and controls.

Unlike the traditional brick-and-mortar shopping environment, where shoppers are surrounded by various dimensions and points of contact like general interior variables, in-store advertisement and promotion, and interaction with shop assistants during the buying process, online shopping is a human-machine interactive buying process where shoppers have to and probably only interact with the retailer's website during the entire buying process. As a result, the website is crucial in the context of online purchasing. It is the intermediary between the online consumers and the product, influencing the online buying intention and consumer perception of product quality and perceived risk, and attracting and retaining online customers [5].

A web environment also affects online shoppers' shopping experiences, influences the time and money they spend on the online portal, and provides the opportunity for online retailers to differentiate from their competitors in the intensely competitive e-commerce market [6]. Website stimuli, or communication between consumers and e-commerce websites, is not only limited to the primary visual appeal dimensions like the design and layout of the website but also includes the use of recommender systems and search mechanisms to increase shopping convenience and deliver a personalized online shopping experience. Recommender systems are artificial intelligence systems that use the consumer's feedback and buying behavior information to infer customers' preferences and automatically suggest products they are likely to buy [7], while the search mechanism uses the information generated by the website [8].

Aragoncillo and Orús [9] believe that recommender systems can trigger emotional and unconscious responses that lead to impulse buying behavior. Park *et al.* [10] also revealed that shoppers buy more impulsively in an online context compared to in traditional retail settings. Internet shoppers and non-internet shoppers are behaviorally apart; hence, it is crucial to distinguish between these two demographics, particularly in today's scenario, which sees the increased usage of the internet and expects consumers to increase the use of the internet in their shopping decisions. The upward trend of using the internet as a sales medium has seen nearly two out of three of the European population experience buying online [9]. The different levels of lockdown and social distancing measures implemented in various countries since the COVID-19 outbreak started at the end of 2019 have also shifted consumer buying behavior, resulting in a surge in e-shoppers and an increase in e-impulse. McKinsey & Company [11] reported that the online shopping habit would

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remain as consumers in the United States intend to shop online even after the pandemic. As consumer impulse buying is significant to companies' revenues, it would be worth exploring this phenomenon in the virtual world.

In a systematic literature review of past scholars' research on impulse buying in a virtual context, defined online impulse buying as "a sudden and immediate online purchase with no pre-shopping intentions" [8]. The main concepts and characteristics of an impulse purchase in an offline context, like unplanned, response to stimulus, and spontaneous reaction, are also applicable in the online context. However, the triggers or stimuli of impulse purchase between the online and offline paradigms are different. In a review of past studies, Zhao *et al*. [5] found that websites, marketing, and affective affect are the three main types of stimuli for online impulse buying.

This study is concentrated in the Malaysian context and focuses on urban areas. Malaysia is a focus country with high internet usage and a dramatically growing number of digital customers. A source from the [12] stated that 96.8% of Malaysians aged 15 years and above used the internet in 2021. The country is also leading among Southeast Asian (SEA) countries in online shopping, with 88% of the nation's total population being digital consumers, ahead of the regional average of 78%. Thus, the scope of this study will cover online buying in a business-to-consumer e-commerce context, which includes the use of a web browser or a mobile app as the interface to carry out the purchase of products and services over the internet. There are two research questions in this study:

Research Question 1: What are the website stimuli that lead to customer satisfaction in the online buying context?

Research Question 2: How does customer satisfaction affect online impulse buying?

As online buying is becoming the new normal in today's digital age and is expected to grow strongly in the future, understanding the factors and determinants that will impact consumers' purchasing decisions and spending in the online context is crucial for internet businesses. Therefore, this study is expected to contribute to understanding the factors that lead to customer satisfaction in the online buying context.

II. Literature Review

This paper uses a Stimulus-Organism-Response (S-O-R) model to investigate online impulse buying. Website stimuli, recommender system, information search, customer service, and privacy and security, have been considered as the stimulus or independent variables that will influence online buying behavior, mediated by customer satisfaction. In the S-O-R model, the organism acts as an intervening variable that evokes an individual inner emotional reaction, and past studies demonstrated that a firm's offering and its customer behavioral outcome are mediated by customer satisfaction [13]. Customer satisfaction is therefore proposed as an organism in this study, which ultimately affects the external behavioral responses – online purchase behavior.

A. The Influence of Recommender System on Customer Satisfaction

Recommender systems ease the consumer's search for products that match their preferences and interests and improve their decision-making in the buying process and satisfaction. A consumer also feels more pleasure and is motivated by the reliable products recommended by the systems [14]. Roudposhti *et al*. [15] also found that the recommender system helps and provides the consumer with a smoother purchase decision. Besides arriving at the same finding on the improved buying decision process and quality, Isinkaye *et al*. [16] also found that recommender systems help a consumer reduce search costs to find and select items in an online buying environment.

Studies also proved that customized content like personalized advertisements, offers, and product recommendations is valued by the consumer. A recent study by [7] on impulse buying in the mobile device context during the COVID-19 pandemic also found that personalized recommendations positively correlate with consumers' perceived enjoyment and arousal. Therefore, this study hypothesized the following:

H_1: Recommender system has a positive influence on customer satisfaction.

B. The Influence of Information Search on Customer Satisfaction

Compared with visiting a physical store to gather the necessary information, online information search is cheaper, reducing the consumer search cost [17] Online information search also allows consumers easy access to price and product information and supports them in making more precise purchase decisions. A pre-purchase information search helps consumers achieve cost savings by buying at a lower price, increasing the chance of getting a superior product by filtering out substandard alternatives, and yielding more satisfaction with improved purchase decisions.

It is common that some consumers may not like to interact with the salesperson, as the latter will try to peruse them to make a purchase. An online information search can then assist this kind of consumer with the freedom from physical contact with sales staff [17]. Consumers also found themselves enjoying novel options with personalization content when looking for commercial information; these options include company websites, newsletters, and social media content [18]. Online information searching also has a positive influence on human hedonic cognition. Research by Yale University revealed that "online information searches may make people feel smarter than they actually are". Thus, this study hypothesized the following:

H_2: Information search has a positive influence on customer satisfaction.

C. The Influence of Customer Service on Customer Satisfaction

Liu *et al*. [19] believe that customer service is the main component in affecting customer satisfaction. The level of contentment will be decreased if there is a delay in response or ignorance of the customers' concerns and inquiries. A more recent study in the Vietnamese e-commerce context also found a similar finding. Consumers value a website's willingness to fix their problems and responsiveness to their inquiries; thus, customer service is one of the most influential determinants of online customer satisfaction [20]. Rahi *et al*. [21] also pointed out that customer service is critical in the online buying process and is also among the most influential factors that drive internet banking adoption in Pakistan, mediated by customer satisfaction. Thus, this study hypothesized the following:

H_3: Customer service has a positive influence on customer satisfaction.

D. The influence of Privacy & Data Security on Customer Satisfaction

Hussain *et al*. [22] pointed out that consumers do not feel safe when using the IoT service, and security and privacy are the two main root causes. Hidayat *et al*. [23] also believe that security and privacy are determinants of online customer satisfaction. A consumer is only willing to visit an online store if they are confident in the portal's ability to protect and not misuse their personal information and credit card data, and how well an online seller safeguards their customer information will impact customer satisfaction [24]. Improper access and unauthorized secondary use of personal data also have increased attention from consumers, and these factors indirectly affect the consumers' intent to continue the use of IoT services.

An experiment conducted in the Netherlands in 2017 and 2018 also arrived at similar findings, revealing that online users increased their concern about the mobile application on their smartphones monitoring their activities and collecting too much personal information, which may be used for other purposes and shared with others without their prior notice and authorization [25]. Therefore, this study hypothesized the following:

H_4: Privacy and data security has a negative influence on customer satisfaction.

E. The Influence of Customer Satisfaction on Online Impulse Buying

Consumers' purchase attitudes and repurchase intentions are significantly affected by their satisfaction. Satisfaction leads to purchase intention, affects spending on a website, and is a major driver for continued purchase intention. A satisfied consumer may cross-buy other related products or services from the same website. An analysis of the consumers on American-based e-commerce sites also delivered similar results: the higher the satisfaction, the more money will be spent by consumers [26]. Past studies also proved that unplanned spending and impulse purchasing are associated with hedonic shopping motivation. Hedonic shopping motivation relates to shoppers' emotional response and sensory pleasure and was found to positively and significantly affect online customer satisfaction [27]. Consumers make more unplanned purchases when they perceive higher hedonic shopping motivation, such as pleasure, enjoyment, and satisfaction, during the online shopping process.

In their qualitative research on online impulsive fashion customers in the Swedish context, found that the joy of commercial website browsing can be seen as a source of instant satisfaction and lead to impulse purchases [28]. A questionnaire-based study on the Taiwanese online impulse buying context found that the customer is both a system user of the online selling platform and, at the same time, an impulse buyer when they buy online; therefore, there is a connection between their satisfaction with the e-store design and their performance with impulse buying behavior [29]. Thus, this study hypothesized the following:

H_5: Customer satisfaction has a positive influence on online impulse buying

F. Customer Satisfaction as Mediator between Website Stimuli with Online Impulse Buying

Bressolles *et al.* [30] revealed that the impact of website dimensions, including personalized settings and privacy and security, on online impulse buying is mediated by customer satisfaction. More recent studies from Hiranrithikorn and Banjongprasert [31] also found that hedonic motivation, which relates to customer satisfaction, mediates the relationship between website attributes and consumer buying impulsively over the internet. Thus, this study hypothesized Table 1 and Fig. 1:

H_6: Customer satisfaction mediates the relationship between website stimuli and online impulse buying. Website stimuli consist of (a) recommender system, (b) information search, (c) customer service, and (d) privacy & data security.

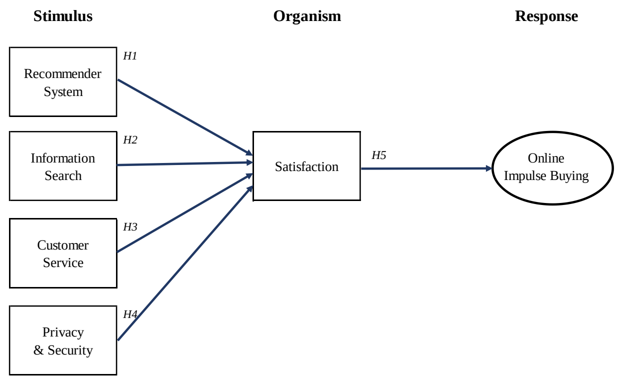

Fig. 1. Theoretical framework.

Table 1. Summary of hypothetical relationship

Hypothesis	Hypothesis Relationship
H_1	Recommender System → Customer satisfaction
H_2	Information Search → Customer satisfaction
H_3	Customer Service → Customer satisfaction
H_4	Privacy & data Security → Customer satisfaction
H_5	Customer Satisfaction → Online Impulse Buying
H_6	Website Stimuli → Customer satisfaction → Online Impulse Buying

III. METHODOLOGY

A quantitative research design is proposed to test the framework and hypotheses. The population of this study is therefore targeted at Malaysian online shoppers aged above 18 years old. Rahi *et al.* [21] believe that a sample size of 200 is considered reasonable, and 300 and 500 are regarded as good and very good. Therefore, a minimum sample size of 300 valid responses is proposed for this study to achieve a better representation of results.

This research adopted a purposive sampling technique. Purposive sampling, also known as judgmental sampling, is a non-probability method. It is a sampling technique "used to select respondents most likely to yield appropriate and useful information". The method is suggested for the study because it effectively uses research resources. Instead of reaching out to a random sample, which may be largely ignored and unable to provide the input that satisfies the researcher's needs, the purposive sampling method acquires in-depth information from those who are in a position to give it, helping to overcome the limitations of current research like resource constraints and short completion timelines.

A questionnaire is used in this study in order to examine the research questions. The duration of disturbing the questionnaire to the respondents are from September 2022 until December 2022. As the purpose of this study is to determine how webpage stimuli affect online impulse buying, it is therefore necessary to include a screening question to filter out respondents who have no online buying experience. Questionnaires in the format of Google Forms were distributed to potential respondents via email, WhatsApp, and Telegram. The survey is self-administered so that respondents can complete it at their convenience.

SPSS and SmartPLS are the two statistical software programs used in this study to perform the data analysis. Upon completion of data collection, the questionnaire is exported from Google Forms to a spreadsheet format. The collected data is then screened and cleaned for errors like missing data. The analysis in SPSS began with the Cronbach's alpha test and factor analysis. Cronbach's alpha test assesses the reliability of the variables, while factor analysis tests the instrument's validity and provides the opportunity to remove any redundant or duplicate items. Once the reliability and validity of the constructs were ascertained, descriptive analysis was performed to gain an understanding of the frequency, percentage, mean, median, and standard deviation for the demographics of the respondents and also the respondent's online buying patterns.

The analysis then proceeded to the next phase using partial least squares structural equation modeling (PLS-SEM) with SmartPLS to evaluate the measurement and structural model of this study. SmartPLS is statistical software that tests the interrelationship between variables, including latent variables and indicator variables, and possesses the advantage of handling complex models and a lower sample size requirement [32]. PLS-SEM is a statistical technique widely used in marketing and other social sciences fields, bringing the advantage of maximizing the amount of explained variance of the endogenous constructs embedded in a path model. The statistical technique is also a preferred and superior approach for mediation analysis; hence, it may be a good fit for the present study since mediation analysis is needed to test the hypothesis 6 (H6).

IV. Results and Discussion

A total of 403 responses were collected by the self-administered survey. The demographics of the respondents are reported in Table 2:

Table 2. Respondents' demographics

Category	Sub-Category	Frequency (n=403)	Percentage (%)
Age	18–29	116	28.8
	30–39	125	31.0
	40–49	135	33.5
	50 and above	27	6.7
Gender	Male	165	40.9
	Female	238	59.1
Education Level	Secondary/High School	37	9.2
	Diploma	55	13.6
	Undergraduate (Degree)	261	64.8
	Post-graduate (Master or PhD)	50	12.4
Monthly Household Income	Less than RM 4,850 (B40)	124	30.8
	Between RM 4,850 to RM 10,970 (M40)	168	41.7
	More than RM 10,971 (T20)	111	27.5
Frequency of Online Buying in A Month	Never	11	2.7
	1–2 times	252	62.5
	3–4 times	89	22.1
	5 times or more	51	12.7
Monthly Spend on Online Buying	Less than RM100	97	24.1
	RM100–RM200	143	35.5
	RM201–RM300	87	21.6
	RM301–RM400	29	7.2
	RM401–RM500	13	3.2
	More than RM500	34	8.4
Online Shopping Site Respondent Buy the most	Lazada	94	23.3
	Shopee	266	66.0
	Taobao	19	4.7
	Zalora	3	0.7
	Retailer own website (Eg: Jaya Grocer, Lenovo, Uniqlo)	8	2.0
	Others	13	3.2
Product Category Respondent Buy the Most from Online Shopping Platforms	Electronics (Eg: Smartphone, tablet, laptop, home appliances & electronic)	61	15.1
	Fashion and beauty	85	21.1
	Food, grocery, and personal care	147	36.5
	Furniture and appliances	15	3.7
	Sports, Toys, DIY and hobbies	36	8.9
	Travel (including accommodations)	2	0.5
	Video games & digital music	4	1.0
	Others	53	13.2

Reliability and validity are the two most essential and fundamental features to assess any measurement instrument or tool for quality studies. Reliability refers to the degree of consistency and is the "consistency or stability of a measure across different samples". Among a number of measures, Cronbach's alpha internal consistency reliability, which describes the correlation of the items in a test to each other, is a common and widely used method to measure the reliability of a measure. The higher inter-relatedness of the items within a questionnaire, the higher the alpha value and a value between 0.70 to 0.95 are regarded as acceptable. The alpha value presented in Table 3 below revealed that the questionnaire used in the study has good reliability, with all the items for each construct having a Cronbach's alpha value above 0.7.

Table 3. Reliability analysis

Constructs	Number of items	Cronbach Alpha
Recommender systems (RS)	7	0.868
Information Search (IS)	7	0.895
Customer Service (CS)	5	0.852
Privacy & Data Security (PS)	8	0.886
Customer Satisfaction (SAT)	7	0.919
Online Impulse Buying (OIB)	7	0.903

Validity is about what an instrument measures, and the degree of accuracy to which a concept is measured in quantitative research. The result in Table 4 reported that the suitability of applying factor analysis for the current study as the KMO index was 0.899, which is well above the accepted limit of 0.6, and Bartlett's test of Sphericity was significant at 0.00, which is less than the threshold of statistically significant 0.05.

Table 4. KMO and Barlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.899
Bartlett's Test of Sphericity	Approx. Chi-Square	10862.419
	Sig	0.000

The study adopted Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS version 4.0 to test the model. In PLS-SEM, the examination of cross-loadings and the Fornell-Larcker criterion are the two traditional approaches widely used for assessing discriminant validity. Heterotrait-Monotrait (HTMT) criterion is another method that offers greater sensitivity to detect discriminant validity problems. As cross-loadings and the Fornell-Larcker criterion may sometimes substantially overstate the presence of discriminant validity [33], this study uses the HTMT criterion for discriminant validity testing. The empirical result also shows that HTMT is a proven method that delivers better performance compared to the two traditional approaches and also the method recommended by scholars for establishing discriminant validity [33]. Discriminant validity assessment by mean of the HTMT criterion measures the ratio of correlation between constructs, and a value higher than 0.85 may indicate a discriminant validity problem. From the results presented in Table 5, the ratio values of this study are all within the acceptable limit. Therefore, the discriminant validity of the construct in this study was confirmed.

Table 5. Discriminant validity—Heterotrait-Monotrait Ratio (HTMT)

	RS	IS	CS	PS	SAT	OIB
IS	0.694					
CS	0.429	0.573				
PS	0.181	0.144	0.077			
SAT	0.631	0.659	0.487	0.133		
OIB	0.252	0.207	0.170	0.051	0.151	

A. *Structural Model Assessment*

Establishing a high predictive model is always challenging for social science studies that deal with human behavior, given that human behavior tends to vary due to individual self-interest, group dynamics, feelings, and other factors and is subject to change over time [34]. Besides, any field that attempts to predict human behavior may expect a low R-squared value, and some of these studies even find it difficult to achieve an R-squared value above 25%. In addition, Ozili [34] suggested that an R-square range between 10% and 50% is acceptable, provided some or most of the explanatory variables are statistically significant. On this basis, the 44.3% R-squared percentage explaining customer satisfaction from website stimuli in this study is acceptable. However, the low R-squared value that customer satisfaction only explained 2.1% of online impulse buying suggests that more non-correlated mediated variables need to be added to the model to better explain online impulse buying behavior.

Besides the R-square value, the structural model assessment also checked Stone-Geisser's Q-square value, commonly referred to as Q-square (Fig. 2). Q-square evaluates the model prediction quality or accuracy of the adjusted model, and a model with a Q-square value greater than zero is deemed predictively relevant. The Q-squared values for the constructs of customer satisfaction and online impulse buying are 0.423 and 0.031, respectively. As these Q-squared values are all above zero, the model's predictive relevance is assured. [33]) state that a Q-square value of 0.02, 0.15, and 0.35 indicates small, medium, and large predictive values, respectively. Therefore, the predictive relevance of the customer satisfaction construct can be considered strong, whereas the predictive relevance of online impulse buying was found weak. The R-squared and Q-squared values for this study are summarized in Table 6.

Table 6. Predictive capabilities assessment—R-Square and Q-Square

Hypothesis Relationship	**R-Square**		**Q-Square**	
Website Stimuli → Customer satisfaction	0.443 > 0.10	Acceptable	0.423 > 0.35	Large
Customer Satisfaction → Online Impulse Buying	0.021 < 0.10	Weak	0.031 > 0.02	Weak

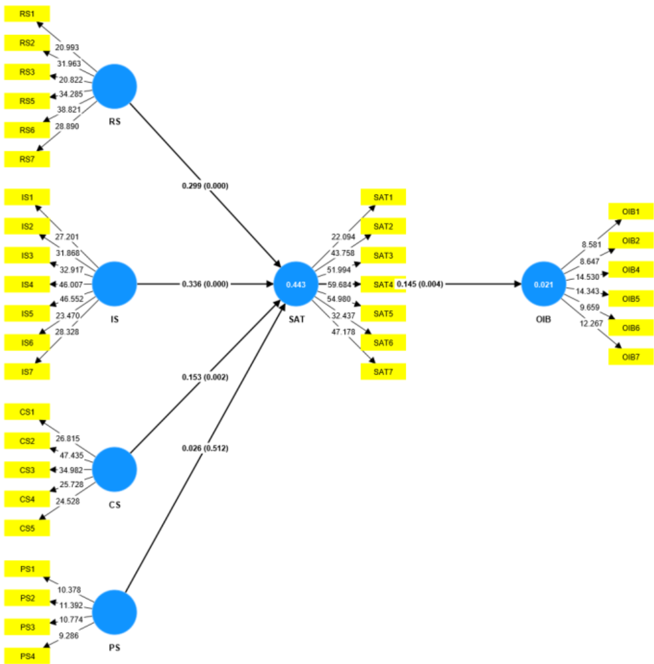

Fig. 2. Structural model assessment.

B. *Hypotheses Testing Results*

The result revealed that the path coefficient between customer satisfaction and online impulse buying is positive and significant ($\beta = 0.145$; t-statistic = 2.887; p-value = 0.004), therefore H5 is accepted. Furthermore, the findings including the path coefficients, t-statistics, p-value and decision to reject or support the hypothesis testing are summarized in Table 7.

This study discovered that the recommender system significantly positively affects customer satisfaction in online shopping. The finding aligns with the investigations of [35], which found that recommender systems enhanced customer satisfaction by providing accurate recommendations. The finding is also supported by the literature of [36], who concluded that the perceived usefulness of the recommender system by online shoppers leads to customer satisfaction.

Table 7. Results of hypothesis testing

Hypothesis Relationship	Path Coefficient	T-Statistics	P-Value	Results
H_1: Recommender System → Customer satisfaction	0.299	4.993	0.000	Supported
H_2: Information Search → Customer satisfaction	0.336	5.233	0.000	Supported
H_3: Customer Service → Customer satisfaction	0.153	3.072	0.002	Supported
H_4: Privacy & Data Security → Customer satisfaction	0.026	0.656	0.512	Not Supported
H_5: Customer Satisfaction → Online Impulse Buying	0.145	2.887	0.004	Supported

Past literature has revealed that the more extensive and higher quality of information made available to consumers during the buying process has led to higher online customer satisfaction [23, 37]. Furthermore, the results of the present study also indicate that information search is positively and significantly related to customer satisfaction. The findings are consistent with [24] study.

The present study also arrived at the same finding as the studies of [23], which confirmed that customer service was significant to online customer satisfaction. The findings of the present study are also similar to those of [37] who found that there was a strong association between responsive customer service and online customer satisfaction. The finding is further supported by the literature of [38]. Kwak *et al.* [38] found that using an AI chatbot to support the customer in a mobile buying context significantly affects customer satisfaction via characteristics like social presence, playfulness, and usefulness.

However, the hypothesis for privacy and data security was rejected. Privacy and data security are not antecedents of online customer satisfaction. The finding contradicts the research of [23] who found that privacy and security were significant antecedents of online customer satisfaction in the internet marketplace. The contradiction may be explained by consumers considering security a prerequisite for online stores, hence it does not trigger their satisfaction. Another possible reason for the inconsistent finding may be that consumers may gain trust in online buying security after they have engaged with online shopping services for a long period of time [24], and this is the current situation in the country as many Malaysians have picked up buying online since the COVID-19 pandemic emerged in early 2020. An earlier study by [24] also arrived at a similar finding: though security is one of the determinants that directly influence online purchase customer satisfaction, the relationship is rather weak.

Besides that, the current study identified that customer satisfaction is a significant determinant of online impulse buying. This finding is consistent with the previous literature of [26], who pointed out that satisfied online shoppers tend to increase their spending on e-commerce. The work of [36], which discovered that customer satisfaction delivered by a recommender system has a positive association with unplanned purchase behavior, also supports the present study's finding.

V. Conclusion

This study identifies the influence of website stimuli on customer satisfaction and consumers' impulse buying behavior in an online buying context. Past literature mainly focuses on website design and quality dimensions like visual appeal, website navigability, ease of use, etc.; therefore, this study shares insight into how advanced technology-supported website stimuli influence consumers to buy impulsively. Four hypotheses were found significant in the relationship and accepted; the other two were not. The results depicted that the recommender system, information search, and customer service had a positive and significant effect on customer satisfaction, and customer satisfaction significantly impacted online impulse buying behavior. The analysis also reveals that, though there was no mediation effect of customer satisfaction between website stimuli and online impulse buying, a direct impact was identified between the recommender system and online impulse buying. Privacy and data security were not found to be determinants of customer satisfaction or online impulse buying. With the increasing trend of people shifting their shopping habits from the traditional brick-and-mortar setting to a virtual context, more businesses have taken their business online nowadays, resulting in increased competition in the e-commerce market. In order to stand out in the highly competitive e-commerce market, online retailers need to customize a web environment that offers a superior shopping experience and can influence the consumer's purchase decision. Although all these businesses rely on the design and quality dimensions of websites, such as visual appeal, website navigability, ease of use, etc., to improve the customer shopping experience, the website stimuli supported by advanced machine learning and AI technologies can play an essential role in delivering a satisfying online shopping experience and promoting consumer impulse buying. As artificial intelligence, machine learning, and other underlying technologies continue to advance, it is also crucial for online retailers to keep up with the developments and explore how they can leverage the advancement of these technologies to customize a web environment that delivers a satisfying online shopping experience and promotes consumer impulse buying. This will eventually help them generate more sales, stay competitive, and enhance their business's viability. Future research may need to incorporate more independent and mediating variables, to increase the proportion of variances explainable by the model.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S. W. Phoong and G. S. Hoo conducted the research; G. S. Hoo performed the data analysis. S. W. Phoong was in charge of overall direction and planning. S. W. Phoong and G. S.

Hoo wrote the paper; all authors had approved the final version.

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