INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue I January 2025

How Customers Decide: Unveiling the Drivers of Customers' Online Purchase Behavior on Online Food Delivery Apps

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DOI: https://dx.doi.org/10.47772/IJRISS.2025.9010154

Received: 30 December 2024; Accepted: 03 January 2025; Published: 08 February 2025

ABSTRACT

Online Food Delivery (OFD) applications have become integral to modern consumer behaviour, offering convenience in food and beverage purchases. However, challenges such as inconsistent user experiences, safety concerns, unreliable delivery, and food quality issues continue to impact customer satisfaction and purchase behaviour. This research explores the factors influencing Customers' Online Purchase Behaviour (COPB) on OFD platforms in Malaysia, using the Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. Data was collected through convenience sampling from OFD users in the Klang Valley region, and analysed using descriptive and inferential statistics via the Statistical Package for Social Sciences (SPSS) and Partial Least Squares Structural Equation Modelling (PLS-SEM) respectively. The findings indicate that Social Influence, Hedonic Motivation, Price Value, Habit, and Trialability significantly impact COPB. Among these, Social Influence had the strongest positive effect ($\beta = 0.171$, $p < 0.001$), suggesting that users' decisions are strongly influenced by the perceptions of others. However, Performance Expectancy, Effort Expectancy, and Facilitating Conditions were not found to significantly influence COPB. This lack of significance could be attributed to the mature technological infrastructure in Malaysia and the normalization of OFD applications. The study concludes that OFD service providers should focus on enhancing social connections, user enjoyment, competitive pricing, and habitual usage to boost customer satisfaction and loyalty. This research offers valuable insights for industry practitioners and suggests areas for future research, particularly regarding the role of performance-related factors in a mature market context.

Keywords: online food delivery (OFD) applications, performance expectancy, effort expectancy, social influence, customer online purchase behavior

INTRODUCTION

The rapid advancement of internet technologies and the proliferation of smartphones have significantly transformed consumer behavior, particularly in the foodservice industry. Online Food Delivery (OFD) applications, as a result of this technological revolution, have emerged as a pivotal tool, offering convenience, efficiency, and accessibility in purchasing food products. Rooted in the broader evolution of the internet and e-commerce, OFD apps leverage digital platforms to meet the demands of urban consumers with fast-paced lifestyles, enabling them to order meals effortlessly via smartphones [1], [2]. These applications provide extensive options, real-time tracking, reviews, and up-to-date restaurant information, effectively reducing the effort required to access food services [3]. The COVID-19 pandemic further accelerated the adoption of OFD services, as restrictions on dining-in heightened the demand for contactless delivery options [4], [5]. In Malaysia, popular OFD providers like Foodpanda and Grab Food exemplify how these platforms cater to diverse consumer needs while influencing purchase behaviors [6]. This underscores the need for well-designed OFD applications that not only ensure service and product quality but also foster customer satisfaction and loyalty, which are critical for sustaining their growth in an increasingly competitive market [7], [8]

Problem Statement

The COVID-19 pandemic significantly affected the global restaurant industry, with countries such as Malaysia implementing Movement Control Orders (MCO) that restricted dine-in options [9]. This led many consumers to turn to online food delivery (OFD) applications as an alternative [9]. The impact of the pandemic was particularly evident in the sharp decline of full-service restaurant traffic, with some regions, like Massachusetts, completely banning on-premise dining, while others like Saudi Arabia closed many public spaces [10]. As businesses faced financial strain, companies such as Uber Eats introduced support measures like daily payouts and fee waivers for small restaurants [11]. The forced adaptation to new sales channels, including OFD apps, was critical for survival during this volatile period, with many restaurants relying on these platforms to maintain profitability[12]. In the United States, the restaurant industry was growing before the pandemic but experienced a significant shift towards food delivery during lockdowns, a trend that continued into 2021 [13].

Despite the transition to the endemic phase in Malaysia in April 2022, which lifted many restrictions, the demand for OFD applications remained strong [14]. The convenience of food delivery continues to appeal to consumers, with platforms like Grab Food and Foodpanda seeing significant increases in orders during and after the MCO [15]. However, the rise in usage also led to more complaints regarding service inconsistencies, security concerns, and poor food quality, which negatively impacted customer satisfaction and purchase intentions [16], [17]. These issues highlight the importance of understanding the factors influencing customer satisfaction and online purchasing behavior, which is crucial for the survival of service providers in the OFD market [18], [19]. Despite the importance of OFD services in Malaysia, there is a noticeable gap in research on consumer behavior in this context, particularly among urban populations [4]. This study aims to fill this gap by investigating the factors influencing Malaysian consumers' purchase intentions and behavior, while also providing insights for restaurant operators to improve service quality and customer satisfaction [20], [21].

Research Objectives

The primary objective of this study, as highlighted by the discussed issues, is to analyze customers' experiences in utilizing OFD applications for purchasing food products, with a specific focus on the factors influencing their online purchase behavior.

1. To examine the effect of Performance Expectancy (PE) towards customer online purchase behavior on OFD applications.
2. To inspect the effect of Effort Expectancy (EE) towards customer online purchase behavior on OFD applications.
3. To assess the effect of Social Influence (SI) towards customer online purchase behavior on OFD applications.
4. To determine the effect of Facilitating Condition (FC) towards customer online purchase behavior on OFD applications.
5. To identify the effect of Hedonic Motivation (HM) towards customer online purchase behavior on OFD applications.
6. To investigate the effect of Price Value (PV) towards customer online purchase behavior on OFD applications.
7. To examine the effect of Habit (HB) towards customer online purchase behavior on OFD applications.
8. To examine the effect of Trialability (TB) towards customer online purchase behavior on OFD applications.

LITERATURE REVIEW

Online food delivery (OFD) applications, a significant e-commerce innovation in the food and beverage industry, have transformed how food is served to customers, offering convenience and efficiency through online platforms that connect restaurants with consumers [1], [22]. The competitive landscape of the OFD market is evident in countries like India, with its $350 billion food industry, and Malaysia, where the market is expected to grow by 14.28% over the next few years, driven by major players like Grab Food and Foodpanda, which collaborate with local eateries and offer promotions to attract customers [23], [24]. In Malaysia, while OFD usage surged during the pandemic, peaking during festive periods like Ramadan, it saw a decline to 29% in Q1 2023 as dine-in options resumed; however, demand remains ongoing, reflecting consumers' lifestyles and preference [24]. Research highlights convenience as a critical factor influencing consumer behavior, with user-friendly applications significantly boosting satisfaction and sustained usage [4], [20]. Yet, gaps remain in understanding OFD behavior across diverse urban and rural demographics in Malaysia [4], [25]. To address these gaps, future studies should adopt longitudinal approaches to capture evolving consumer attitudes, particularly during transitional periods like the endemic phase of COVID-19 [26], [27]. This study seeks to advance the field by extending the Unified Theory of Acceptance and Use of Technology (UTAUT2) framework with novel constructs such as Trialability, aiming to enrich academic discourse and provide actionable insights for OFD service providers and restaurant operators.

Underpinning Theory

This study adopts the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework to identify determinants of customer online purchase behavior in the context of OFD applications. UTAUT2, an evolution of the original UTAUT model proposed by reference [28], integrates constructs from earlier theories, such as the Technology Acceptance Model (TAM) [29], Theory of Planned Behavior (TPB) [30], [31], and Diffusion of Innovation (DOI) [31], providing a robust framework to predict technology adoption behavior. While UTAUT explains 70% of the variance in adoption behavior, its extended version, UTAUT2, incorporates additional constructs such as Hedonic Motivation (HM), Price Value (PV), and Habit (HB), making it more relevant for consumer-focused contexts [28], [32]. In the OFD application context, researchers have adapted UTAUT2 by introducing constructs like perceived control, trust, application quality, and convenience to account for user-specific and situational factors [21], [33], [34]. For example, the impact of Performance Expectancy (PE), social influence, and Habit (HB) on continued use of OFD services demonstrated during the COVID-19 pandemic [35]. Addressing gaps in research on consumers aware but indecisive about OFD adoption, this study introduces a modified UTAUT2 model incorporating trialability, aiming to expand understanding of customer behavior and bridge knowledge gaps in the adoption of OFD technologies.

Customer Online Purchase Behavior (COPB)

Customer behavior research aims to understand the key determinants of online purchase behavior, which can vary and evolve over time with diverse consumer perspectives. Reference [30] defined online purchase behavior as the rate at which consumers make online purchases, while reference [30] emphasized that consumer intentions, such as purchase behavior online, reflect the willingness to engage in specific actions. In the context of online food delivery (OFD) applications, satisfied customers can increase their repurchase and revisit intentions [36]. Additionally, further explained that online retailers can encourage repeat purchases by creating engaging online experiences, such as providing detailed product information and high-quality visuals [37], [38]. The findings of this research suggested by reference [39], that customer purchasing behavior in online shopping is influenced by a diverse array of factors, including but not limited to demographic characteristics (such as age and gender), usage patterns, price, convenience, satisfaction, purchase frequency, product type, expenditure, and product quality. In conclusion, the study emphasizes that consumer Habit (HB)s and various influencing factors significantly impact online shopping behavior. Therefore, these factors contribute to customer information satisfaction and purchase intention, ultimately shaping customer behavior online for OFD applications. This research proposes that the influencing factors, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence, Facilitating Condition (FC)s, Hedonic Motivation (HM), Price Value (PV), Habit (HB), and Trialability, all significantly affect customer purchase behavior on OFD applications.

Performance Expectancy (PE)

Performance Expectancy (PE), a key construct in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), is defined as the degree to which customers perceive that using a technology will yield benefits in task performance [32]. This concept aligns with perceived usefulness in the Technology Acceptance Model (TAM), extrinsic motivation in the Motivation Model, job-fit in the Model of PC Utilization, relative advantage in the Innovation Diffusion Theory, and outcome expectations in Social Cognition Theory [40]. In the context of online food delivery (OFD) applications, Performance Expectancy (PE) significantly influences customer purchase behavior and information satisfaction by offering time efficiency, flexibility, and accessibility [18],

[34], [41]. For instance, OFD applications allow customers to order meals conveniently from any location, reducing physical effort and congestion at restaurants, especially during the endemic era [3], [18]. Such features enhance the utilitarian value of these platforms, driving customer satisfaction and shaping new purchasing behaviors [42]. Studies confirm that customers are more likely to adopt and remain satisfied with OFD applications when they perceive them as time-saving and efficient compared to traditional methods [3], [43], [44].

H_1: Performance Expectancy (PE) has an influence on customer purchase behavior online on OFD applications

Effort Expectancy (EE)

Effort Expectancy (EE), also one of a critical construct in UTAUT2, refers to the ease of use associated with a technology, impacting users' willingness to adopt it [28], [45]. Derived from the perceived ease of use concept in TAM, Effort Expectancy (EE) reflects the level of simplicity and minimal effort required for technology usage, influencing both customer behavior and satisfaction [32], [46]. In the context of online food delivery (OFD) applications, Effort Expectancy (EE) enhances user experiences by providing intuitive navigation, real-time order tracking, and efficient delivery systems [47], [48], [49]. Simplified processes such as easy account setup, order placement, and timely updates improve usability and customer satisfaction [3], [18]. Additionally, the convenience and accessibility of OFD applications are crucial in creating positive perceptions and fostering repeat usage [22], [50]. Prior studies highlight that lower complexity in OFD systems significantly influences customer purchase behavior and satisfaction [51], [52], [53]. Hence, Effort Expectancy (EE) emerges as a pivotal factor in driving adoption and satisfaction, leading to the following hypotheses:

H_2: Effort Expectancy (EE) has an influence on customer purchase behavior online on OFD applications

Social Influence (SI)

Social influence, a fundamental construct in UTAUT2, refers to the extent to which individuals perceive that other—such as family, friends, or peers—believe they should use a particular technology, influencing their intention to adopt it [32]. In the context of online food delivery (OFD) applications, Social Influence (SI) plays a crucial role in shaping customers' decisions, as users often rely on suggestions, reviews, and recommendations from their social circles to make informed choices [22], [54]. This dynamic is supported by studies indicating that peer influence and positive opinions from trusted sources significantly impact the adoption and satisfaction associated with new technologies like OFD applications [22], [38]. However, media exposure can also drive usage, highlighting variations in motivational factors [41]. Social Influence (SI) is linked to customers' information satisfaction, as individuals seek validation and guidance from their network before engaging with new systems [54]. The construct aligns with findings that emphasize its impact on both purchase behavior and satisfaction in the adoption of emerging technologies [32], [41]. Based on these insights, the following hypotheses are proposed:

H_3: Social Influence (SI) has an influence on customer purchase behavior online on OFD applications

Facilitating Condition (FC):

Facilitating Condition (FC), as outlined by reference [32], refer to the availability of sufficient resources and support necessary for users to effectively engage with a technology. In the context of Online Food Delivery (OFD) applications, these conditions include the presence of reliable high-speed internet infrastructure, compatibility with various devices, and multiple payment gateways, all of which contribute to facilitating usage [3], [55]. Supporting infrastructure such as internet coverage and compatible devices has been shown to enhance user satisfaction by ensuring smooth transaction processes [56]. Moreover, the quality of the applications, which rely on stable internet connections and the availability of customer support, plays a crucial role in user satisfaction and acceptance [3]. The presence of favorable Facilitating Condition (FC)s is associated with higher customer satisfaction and, in turn, influences online purchase behavior [57]. Consequently, Facilitating Condition (FC)s are a significant determinant of both customer satisfaction and purchase behavior in the OFD context, as supported by previous research [58], [59]. Therefore, this study proposes the following hypotheses:

H_4: Facilitating Condition (FC) has an influence on customer purchase behavior online on OFD applications

Hedonic Motivation (HM)

Hedonic Motivation (HM), as defined by [32], refers to the enjoyment and pleasure derived from using technology, often linked to personal gratification and fun-based incentives. This construct has a significant impact on consumer behavior, especially in the context of Online Food Delivery (OFD) applications, where pleasure-seeking behavior influences the intention to use these platforms [60]. The psychological effects of the COVID-19 pandemic further highlighted the role of Hedonic Motivation (HM), as consumers turned to OFD applications to escape anxiety, isolation, and stress, leading to impulsive or hedonistic consumption behaviors [61], [62]. Additionally, visual appeal and functional design of the OFD app contribute to Hedonic Motivation (HM), enhancing user satisfaction and fostering positive attitudes toward the platform [63], [64]. As a result, Hedonic Motivation (HM), influenced by both psychological factors and app aesthetics, play a pivotal role in shaping consumer satisfaction and online purchase behavior. Furthermore, during the COVID-19 pandemic, Hedonic Motivation (HM) played a crucial role in encouraging consumers to use OFD services, as individuals sought enjoyable and convenient alternatives to traditional dining [65]. These findings underscore the importance of Hedonic Motivation (HM) in shaping consumer behavior and satisfaction in the context of OFD applications. Thus, this study proposes the following hypotheses:

H_5: Hedonic Motivation (HM) has an influence on customer purchase behavior online on OFD applications

Price Value (PV)

Price Value (PV) pertains to the financial considerations consumers evaluate when adopting new technologies, such as online food delivery (OFD) applications. Customers are more likely to adopt a new system when the perceived benefits outweigh the associated costs [3]. In the context of UTAUT2, Price Value (PV) is defined as the cognitive interaction between a consumer's perception of the application's advantages and the associated costs [32]. The rapid growth of OFD applications is attributed to their various advantages, including the ability to deliver food directly to customers' doorsteps, a variety of payment modes, and attractive discounts, incentives, and cashback offers [48]. For instance, OFD service providers like Grab Food employ pricing strategies such as promo codes or exclusive offers to encourage consumers to utilize their services at the lowest price point [66]. However, when customers perceive a product or service as unfavorable or not meeting their preferences, they may experience regret over their purchase decision [67]. Studies have consistently shown that Price Value (PV) influences customer purchase behavior and satisfaction. For example, researcher [68]found that a customer's satisfaction with a product or service is influenced by its price. Similarly, reference [69] noted that pricing significantly impacts customer satisfaction, with consumers often switching brands when a product's pricing value varies. Reference [50] highlighted that Price Value (PV) is a key factor affecting consumers' continuous usage of OFD applications, emphasizing the importance of offering incentives like coupons or discounts on delivery services to encourage continued use. Additionally, researcher [70] found that both price and value consciousness are crucial in predicting consumer behavior and satisfaction, suggesting that lowering price and improving value for money are essential steps in increasing purchases. These findings underscore the importance of Price Value (PV) in shaping consumer behavior and satisfaction in the context of OFD applications.

H_6: Price Value (PV) has an influence on customer purchase behavior online on OFD applications

Habit (HB)

Habit (HB), a significant construct in the UTAUT2 model, refers to behaviors that develop spontaneously through learning and are often influenced by current surroundings or past experiences [71]. In the context of online food delivery (OFD) applications, Habit (HB) is defined as the automatic execution of behavior due to familiarity with these platforms. Prior usage experience is essential for Habit (HB) to impact technology use, making it a crucial element in determining future technology adoption [32]. Studies have shown that consumers' habit predict technology use, with habits serving as a vital alternative mechanism in forecasting consumer behavior [72]. Additionally, Habit (HB) influences customer information satisfaction; individuals with high levels of habit are more likely to make more purchases compared to those lacking such Habit (HB)s [73].

Furthermore, satisfaction from using OFD applications leads to continuous intention, resulting in unplanned use of these platforms [74]. Therefore, managing customers who have used delivery applications is crucial, as prior usage experience is a prerequisite for habit in influencing technology use [72]. To maintain current consumers and prevent them from transferring to another OFD app service, it is necessary to offer a variety of incentives to enhance satisfying experiences. Based on these findings, the following hypotheses are proposed:

H_7: Habit (HB) has an influence on customer purchase behavior online on OFD applications

Trialability (TB)

Trialability (TB) refers to the ability of an innovation to be tested on a small scale before full adoption, which can enhance its acceptance by consumers [75]. The concept suggests that if an innovation allows for testing, the uncertainty surrounding its use is reduced, leading to a more favorable customer response [76]. This is particularly important in the context of online food delivery (OFD) applications, where service providers often offer promotional trials such as vouchers or discounts to encourage adoption and create positive experiences [77]. However, differences in the Trialability (TB)design between new and long-term users of OFD applications could influence user experiences. Despite this, Trialability (TB) remains crucial for first-time users, as it directly impacts purchase intention and customer satisfaction [78], [79]. By providing a risk-free introduction to the technology, Trialability (TB) helps users evaluate the benefits of the service, thereby increasing the likelihood of adoption and satisfaction [79]. Therefore, Trialability (TB) is expected to significantly influence customer online purchase behavior and satisfaction with OFD applications, as supported by previous research on technology adoption [78], [79]. The proposed hypotheses for this construct are:

H_8: Trialability (TB) has an influence on customer purchase behavior online on OFD applications

Proposed Framework

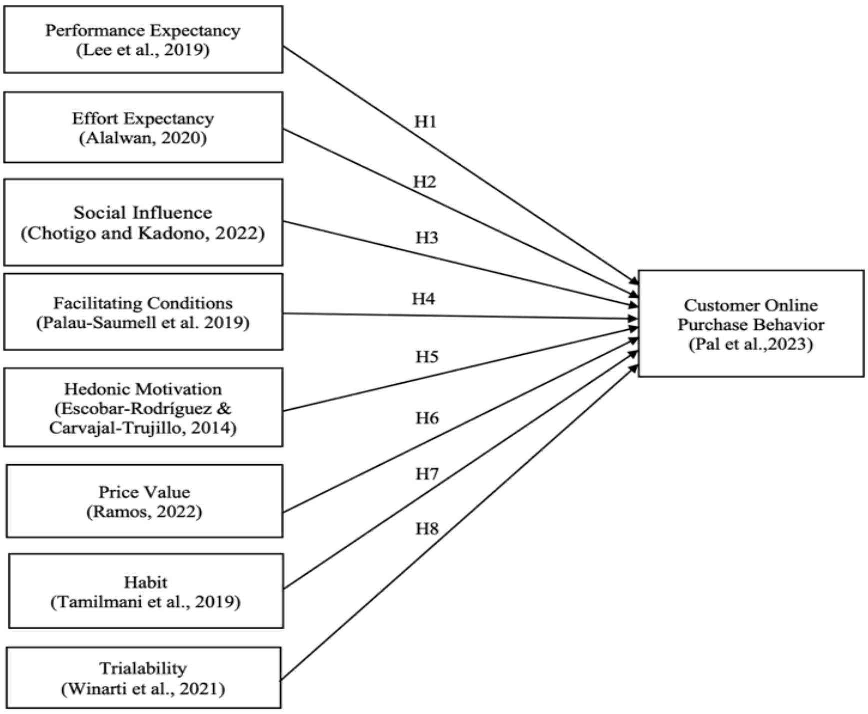

Fig. 1 Proposed Framework

RESEARCH METHODOLOGY

Research Design

In this study, a quantitative research approach is adopted, as defined by reference [80] as the "quantitative or numeric description of trends, attitudes, or opinions of a population." This approach was chosen due to its cost-effectiveness and ability to quickly gather data through surveys, which allow for wider geographic coverage compared to methods like phone calls or in-person interviews [81]. The purpose of this study is to examine the relationship between influencing factors and customer purchase behavior on online food delivery (OFD) applications. The study focuses on consumers who are technologically familiar with the OFD system. It is descriptive and correlational in nature, aiming to outline the characteristics of the variables involved, such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence, Facilitating Condition (FC), Hedonic Motivation (HM), Price Value (PV), Habit (HB), and Trialability (TB) [82]. Data was collected through a Google Forms survey distributed via WhatsApp Messenger and social media platforms such as Facebook, and Instagram, which is an effective method that minimizes bias compared to face-to-face interviews.

Population Sampling and Data Collection Procedure

This study focuses on Foodpanda Malaysia, a leading online food delivery (OFD) application with over 300 employees, 30,000 riders, and more than 25,000 partner restaurants across Malaysia, making it the ideal choice for investigation [83]. The research targets consumers in Klang Valley, a region with a population of approximately 6.14 million, where Foodpanda has seen significant growth [84]. Given the large area and the inability to access all users, convenience sampling was employed to select respondents, as it offers practical and cost-effective data collection [85]. The sample size for this study, calculated using G*Power software, is determined to be 178 respondents. Data will be gathered using an online survey distributed through Google Forms, with respondents accessed via WhatsApp, Facebook, and Instagram, aiming to reduce response bias and improve efficiency. Despite the potential for bias in convenience sampling, the method's feasibility in terms of time and resources justifies its use [85]. The use of online platforms ensures effective data collection from the targeted demographic in Klang Valley, known for its high technological adoption [86].

Instrument Development

As outlined in the previous subchapter, the researcher utilized survey questionnaire as the primary tool for data collection. The design of the questionnaire incorporated variables with the aim of assessing key factors related to online food delivery (OFD) applications. The online questionnaire was structured into six sections: Section A (Demographic Profile), Section B (Influencing Factors) which consists of 8 subsection that covers all the forementioned determinants and Section C (Customer Online Purchase Behavior). The demographic profile section employed a nominal scale, while the remaining sections utilized an interval scale, with items measured on a five-point Likert scale (ranging from 1: Strongly Disagree to 5: Strongly Agree). The variables under investigation include the influencing factors affecting the use of OFD applications, customer purchase intention, customer information satisfaction, and customer online purchase behavior, all of which the questionnaire aimed to evaluate comprehensively.

Table 1 Measurement Items

Section	Code	Description	Number of Items	Sources
A: Demographic Profile	N/A	Gender	8	[48]
		Age		
		Marital Status		
		Highest Education Level		
		Occupation		
		Current based location		
		Frequency in using OFD applications		

		Year OFD application usage		
B: Influencing Factors (Performance Expectancy, PE)	PE1	I find online food delivery applications useful in my daily life.	5	[18]
	PE2	Using online food delivery applications enables me to accomplish the purchasing process more quickly.		
	PE3	I can save time when I use online food delivery applications for purchasing foods		
	PE4	I find online food delivery applications enhance effectiveness in purchasing foods		
	PE5	I find online food delivery applications is fast		
B: Influencing Factors (Effort Expectancy, EE)	EE1	Learning how to use online food delivery applications is easy for me.	5	[3]
	EE2	I find online food delivery applications is easy to use.		
	EE3	It is easy for me to become skilful at using online food delivery applications.		
	EE4	My interaction with online food delivery applications is clear and understandable.		
	EE5	I would find it easy to get online food delivery applications to do what I want it to do.		
B: Influencing Factors (Social Influence, SI)	SI1	People who are important to me think that I should use online food delivery applications for purchasing foods.	5	[22]
	SI2	People who influence my behavior think that I should use online food delivery applications for purchasing foods.		
	SI3	People whose opinions I value prefer that I use online food delivery applications for purchasing foods.		
	SI4	I think I more likely to use online food delivery applications if my family and friends use it		
	SI5	I use online food delivery applications because of my colleagues who use it		
B: Influencing Factors (Facilitating Condition, FC)	FC1	I have the resources necessary to use online food delivery applications.	5	[3]
	FC2	Online food delivery applications are compatible with other technologies I use.		
	FC3	I can get help from others when I have difficulties using online food delivery applications.		
	FC4	I have the knowledge necessary to use online food		

		delivery applications		
	FC5	I have access to relevant information on the use of online food delivery applications		
B: Influencing Factors (Hedonic Motivation, HM)	HM1	Using online food delivery applications for purchasing foods is fun.	5	[41]
	HM2	Using online food delivery applications for purchasing foods is enjoyable.		
	HM3	Using online food delivery applications for purchasing foods is very entertaining.		
	HM4	I feel excited in using online food delivery applications.		
	HM5	Using online food delivery applications is amusing.		
B: Influencing Factors (Price Value, PV)	PV1	I can save money by using online food delivery applications for purchasing foods by comparing the prices offered at different online stores.	5	[50]
	PV2	I like to search for cheap deals at different online stores when I purchase foods through online food delivery applications.		
	PV3	Online food delivery applications provide extensive promotional price for delivery service		
	PV4	Foods product in online food delivery applications is reasonably priced.		
	PV5	Online food delivery applications offer better value for money.		
B: Influencing Factors (Habit, HB)	HB1	Purchasing foods through food delivery applications is almost like a habit for me	5	[74]
	HB2	I must use food delivery applications for purchasing foods.		
	HB3	Using food delivery applications for purchasing foods has become natural to me.		
	HB4	Using online food delivery applications is a part of my daily routine.		
	HB5	I am addicted in using online food delivery applications		
B: Influencing Factors (Trialability, TB)	TB1	Before deciding whether to use any online food delivery applications, I can properly try them out	5	[78]
	TB2	I can experiment with online food delivery applications as necessary.		
	TB3	I do not have adequate opportunities to try out different things on the online food delivery		

		applications		
	TB4	Online food delivery applications were available to me to adequately test run various function.		
	TB5	During my first time using online food delivery applications, there is trial design available		
C: Customer Online Purchase Behavior (COPB)	COPB1	I often using online food delivery applications when I am busy.	8	[3]
	COPB2	I tend to use online food delivery applications because it easy to use.		
	COPB3	I started to use online food delivery applications because I was influenced by peers.		
	COPB4	I often to use online food delivery applications because of the support provided by the applications.		
	COPB5	I naturally use online food delivery applications		
	COPB6	I likely to use online food delivery applications because of fun.		
	COPB7	I likely to purchase foods from online food delivery applications because of lower price		
	COPB8	I tend to use online food delivery applications as I can try before use.		

Data Analysis

After data collection, statistical analysis was performed to identify trends and test the hypothesis. Descriptive statistics first summarize the data, including respondent characteristics like age, gender, and OFD usage by using Statistical Package for Social Sciences (SPSS Software). Inferential statistics then tested the hypotheses by conducting Partial Least Squares Structural Equation Modelling (PLS-SEM). PLS-SEM was chosen for its suitability in predicting the effects of influencing factors on customer online purchase behavior, extending the UTAUT2 framework, and handling the complexity of the model with multiple independent variables. PLS-SEM is a statistical method used to analyze complex relationships between observed and latent variables, particularly in exploratory and predictive research [87], [88]. In this analysis will be involved assessing the measurement model validity (convergent, discriminant, and reliability) and evaluating the structural model using path coefficients, R^2, f^2, and Q^2 for predictive relevance [89], [90].

RESULTS

Demographic Analysis

Table 2 Demographic Analysis

	Frequency	%
Gender		
Male	49	27.5
Female	126	70.8

Prefer not to say	3	1.7
Age		
12 – 18 years old	0	0
19 – 25 years old	113	63.5
26 – 35 years old	52	29.2
36 – 45 years old	10	5.6
46 years and older	3	1.7
Marital Status		
Single	147	82.6
Married	30	16.9
Divorced/Separated	1	0.6
Highest Education Level		
Secondary School	15	8.4
Undergraduate	114	64
Postgraduate	49	27.5
Occupation		
Full-time	81	45.5
Part-time	4	2.2
Unemployed	1	0.6
Self-employed	7	3.9
Student	85	47.8
Geographic Location (Klang Valley Only)		
Yes	178	100
No	0	0
Usage Frequency of OFD Applications		
Once a day or more often	4	2.2
A few times a week	26	14.6
About once a week	17	9.6
2-3 times a month	47	26.4
About once a month	38	21.3
2-3 times a year	46	25.8
Year Usage of OFD Applications		

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue I January 2025

2012 – 2013	1	0.6
2014 – 2015	2	1.1
2016 – 2017	18	10.1
2018 – 2019	59	33.1
2020 – 2023	98	55.1

The demographic analysis of the respondents (N = 178) provides comprehensive insights into their profiles and online food delivery (OFD) application usage. Female respondents dominate the sample (70.8%), with the majority being young adults aged 19-25 years (63.5%) and predominantly single (82.6%). Most participants hold undergraduate (64%) or postgraduate (27.5%) qualifications, with students (47.8%) and full-time employees (45.5%) forming the largest occupational groups. Geographically, all respondents reside in the Klang Valley, reflecting higher familiarity with OFD applications compared to rural populations. Usage frequency data shows moderate engagement, with the majority using OFD services monthly or bi-monthly. Adoption trends reveal significant growth from 2018-2019 (33.1%) and a peak during 2020-2023 (55.1%), likely driven by the pandemic. These findings underline the importance of demographic and usage patterns in shaping consumer behavior in the OFD sector.

Descriptive Statistics

Table 3 Descriptive Statistics

Items Code	N	Overall Mean	Overall Standard Deviation
PE	313	4.23	0.895
EE	313	4.41	0.732
SI	313	3.43	1.164
FC	313	4.25	0.826
HM	313	3.72	1.067
PV	313	3.27	1.187
HB	313	2.63	1.346
TB	313	3.5	1.019
COPB	313	3.43	1.151

This report summarizes the descriptive statistics for key variables based on the overall mean and standard deviation. Based on the table, this report highlights the key insights from the descriptive statistics. Variables such as Performance Expectancy, Effort Expectancy, and Facilitating Conditions received high ratings with low variability, indicating strong agreement. Moderate or low means with higher standard deviations, such as Habit and Price Value, suggest areas of mixed perceptions or potential concern. These results can guide further analysis and targeted strategies for improvement.

Structural Equation Model

Measurement Model

The subsequent section provides an evaluation of the measurement model (Figure 1), detailing the assessment of reliability, convergent validity, and discriminant validity for the reflective constructs by using PLS-SEM.

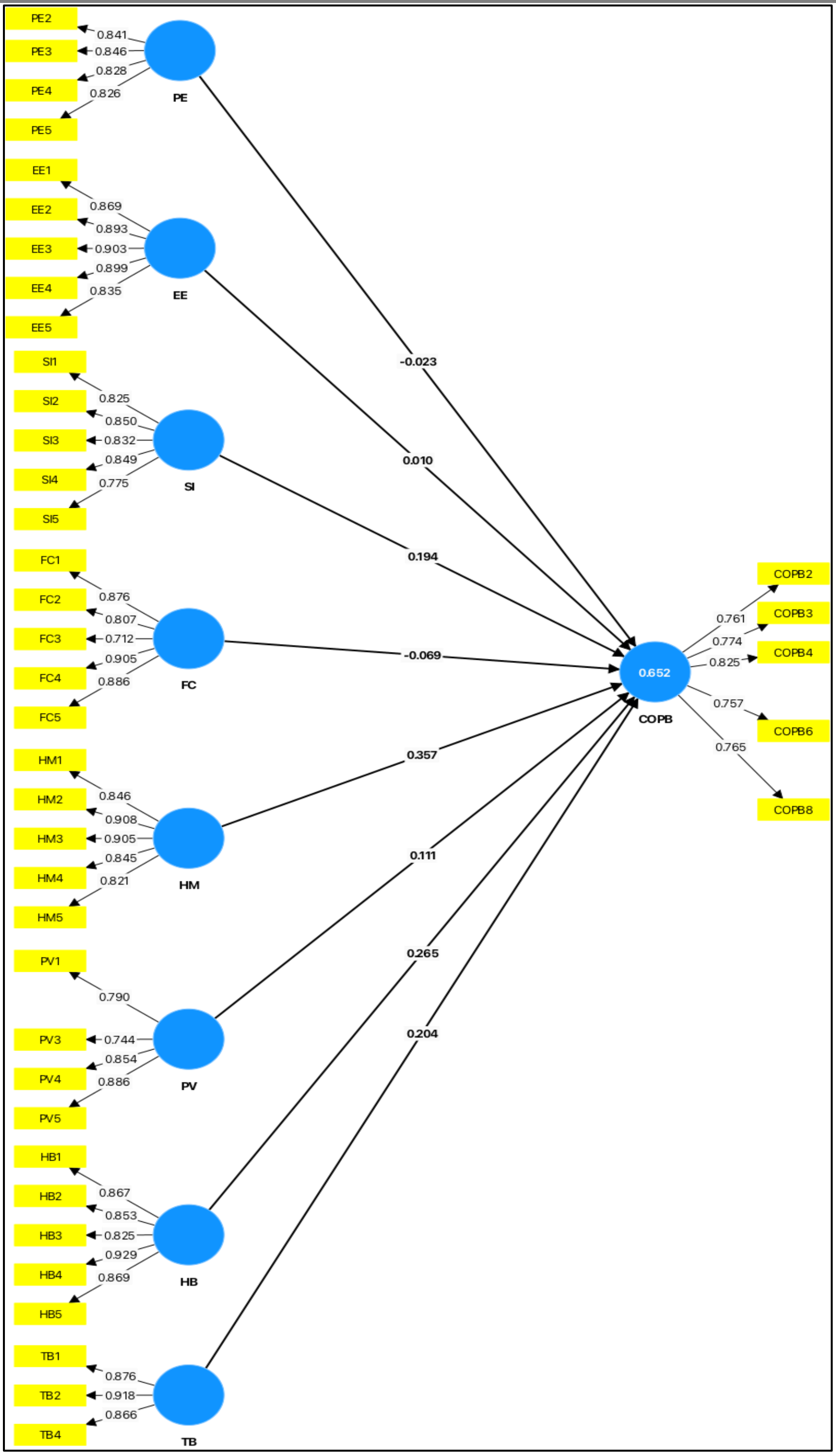

Fig 1 The Measurement Model

Reliability and Convergent Validity

Table 4 Convergent Validity

Construct	Cronbach's alpha	Composite Reliability (CR)	Average variance Extracted (AVE)
Performance Expectancy (PE)	0.856	0.902	0.698
Effort Expectancy (EE)	0.927	0.945	0.775
Social Influence (SI)	0.884	0.915	0.683

Facilitating Condition (FC)	0.895	0.923	0.706
Hedonic Motivation (HM)	0.916	0.937	0.749
Price Value (PV)	0.837	0.891	0.673
Habit (HB)	0.919	0.939	0.756
Trialability (TB)	0.864	0.917	0.787
Customer Online Purchase Behaviour (COPB)	0.835	0.884	0.603

The reliability and convergent validity of the constructs were assessed through Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). All constructs demonstrated satisfactory internal consistency, as Cronbach's alpha values exceeded the threshold of 0.7, ranging from 0.835 (COPB) to 0.927 (EE). Similarly, CR values for all constructs surpassed the recommended threshold of 0.7, indicating strong composite reliability, with values ranging from 0.884 (COPB) to 0.945 (EE). Furthermore, the AVE values for all constructs were above the minimum threshold of 0.5, ranging from 0.603 (COPB) to 0.787 (TB), confirming adequate convergent validity. These results suggest that the measurement model exhibits reliable and valid constructs, ensuring its suitability for further structural analysis.

Discriminant Validity

Discriminant validity refers to the extent to which a construct is empirically distinct from other constructs in a measurement model, ensuring that theoretically different constructs are not highly correlated. It is assessed using criteria such as the Fornell-Larcker criterion or the Heterotrait-Monotrait (HTMT) ratio to confirm the uniqueness of each construct within the model. According to table below, HTMT ratio was conducted to analyse the discriminant validity. Thus, the result was laid out.

Table 5 Heterotrait-Monotrait (HTMT)

	COPB	EE	FC	HB	HM	PE	PV	SI	TB
COPB									
EE	0.327								
FC	0.288	0.739							
HB	0.695	0.165	0.122						
HM	0.746	0.446	0.412	0.423					
PE	0.502	0.649	0.555	0.378	0.562				
PV	0.589	0.07	0.128	0.618	0.384	0.348			
SI	0.656	0.383	0.463	0.506	0.502	0.527	0.42		
TB	0.661	0.463	0.491	0.432	0.562	0.52	0.347	0.494	

Based on the Heterotrait-Monotrait Ratio (HTMT) assessment, the results indicate that all HTMT values are below the commonly accepted threshold of 0.85, confirming discriminant validity among the constructs. The highest HTMT value is observed between Hedonic Motivation (HM) and Perceived Enjoyment (PE) (0.562), while the lowest is between Effort Expectancy (EE) and Perceived Value (PV) (0.07). These findings demonstrate that the constructs in the model are sufficiently distinct from one another, suggesting that they measure separate theoretical concepts. This evidence supports the robustness of the measurement model for further structural analysis.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue I January 2025

Structural Model

Path Coefficient

In Partial Least Squares Structural Equation Modeling (PLS-SEM), the path coefficient represents the strength and direction of the relationship between constructs in the structural model. It indicates how changes in an independent variable predict changes in a dependent variable. Path coefficients range from -1 to +1, where values closer to ±1 denote stronger relationships [91]. Statistical significance of path coefficients is assessed using bootstrapping, with a commonly applied significance level of 5% ($p < 0.05$) [91], [92]. A significant path coefficient suggests that the relationship between constructs is unlikely due to random chance, providing empirical support for hypothesized relationships in the model.

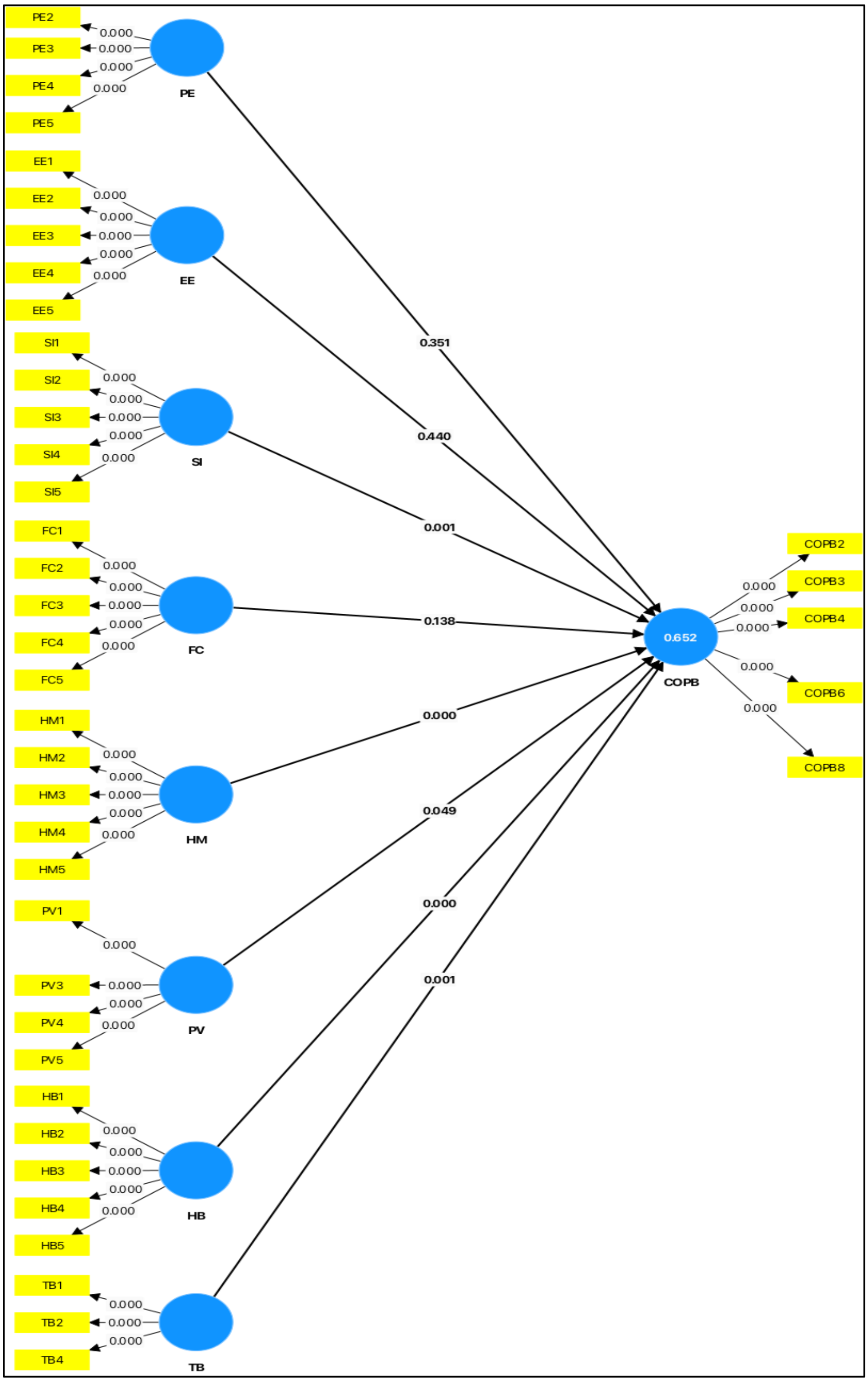

Fig 2 The Path Coefficient

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue I January 2025

Table 6 Path Coefficient

Path Analysis	Original (O)	STDEV	T statistics	P values
PE -> COPB	-0.023	0.061	0.382	0.351
EE -> COPB	0.010	0.065	0.151	0.440
SI -> COPB	0.194	0.064	3.051	0.001
FC -> COPB	-0.069	0.063	1.09	0.138
HM -> COPB	0.357	0.061	5.864	0.000
PV -> COPB	0.111	0.067	1.651	0.049
HB -> COPB	0.265	0.065	4.093	0.000
TB -> COPB	0.204	0.063	3.215	0.001

The path analysis results reveal that Hedonic Motivation (HM, $\beta = 0.357$, $p < 0.001$), Habit (HB, $\beta = 0.265$, $p < 0.001$), Trialability (TB, $\beta = 0.204$, $p = 0.001$), Social Influence (SI, $\beta = 0.194$, $p = 0.001$), and Price Value (PV, $\beta = 0.111$, $p = 0.049$) significantly positively influence Customer Online Purchase Behavior (COPB). In contrast, Performance Expectancy (PE, $\beta = -0.023$, $p = 0.351$), Effort Expectancy (EE, $\beta = 0.010$, $p = 0.440$), and Facilitating Conditions (FC, $\beta = -0.069$, $p = 0.138$) show no significant impact. These findings highlight HM, HB, and TB as primary drivers of COPB. Hence, the hypothesis testing can be summarized in such manner (Table 7).

Table 7 Summary of Hypothesis Testing

Path Analysis	Result
PE -> COPB	Not Supported
EE -> COPB	Not Supported
SI -> COPB	Supported
FC -> COPB	Not Supported
HM -> COPB	Supported
PV -> COPB	Supported
HB -> COPB	Supported
TB -> COPB	Supported

Coefficient of Determinant (R2)

In PLS-SEM, the R-square (R^2) value indicates the proportion of variance in a dependent variable explained by its predictors, ranging from 0 to 1. Higher values reflect stronger explanatory power, with 0.25, 0.50, and 0.75 often interpreted as weak, moderate, and substantial, respectively [91], [92]. It is a key measure of a model's predictive accuracy.

Table 8 The Coefficient of Determination

Variable	R-square
COPB	0.652

The R-square value of 0.652 for Customer Online Purchase Behavior (COPB) indicates that the independent variables in the model collectively explain 65.2% of the variance in COPB. This suggests a substantial level of explanatory power, as over half of the variability in COPB is accounted for by the predictors included in the structural model. Such a high R-square value demonstrates the model's effectiveness in capturing the key determinants influencing COPB.

Effect Size (f2)

In PLS-SEM, the f-square (f^2) measures the effect size of an independent variable on a dependent variable. It indicates the strength of the relationship, with small (0.02), medium (0.15), and large (0.35) effects. f^2 helps assess the practical significance of predictors in the model [91].

Table 9 The Coefficient of Determination

Variable	COPB
PE	0.001
EE	0.000
SI	0.064
FC	0.007
HM	0.219
PV	0.023
HB	0.116
TB	0.073

Based on the table above, the f^2 values for the variables in the model indicate varying degrees of effect on Customer Online Purchase Behavior (COPB). Hedonic Motivation (HM, $f^2 = 0.219$) has a large effect, suggesting it significantly influences COPB. Habit (HB, $f^2 = 0.116$) also demonstrates a medium effect, while Social Influence (SI, $f^2 = 0.064$), Trust in Brand (TB, $f^2 = 0.073$), and Price Value (PV, $f^2 = 0.023$) show small effects. Perceived Ease of Use (PE, $f^2 = 0.001$) and Effort Expectancy (EE, $f^2 = 0.000$) have negligible effects on COPB, indicating their limited practical significance in the model. Facilitating Conditions (FC, $f^2 = 0.007$) similarly exhibits a very small effect.

Predictive Relevance (Q2)

Predictive relevance in PLS-SEM refers to the model's ability to predict key endogenous variables, assessed through the Q^2 statistic [91]. In this analysis, blindfolding procedure was conducted. The blindfolding procedure is commonly used to evaluate predictive relevance by systematically omitting part of the data and using the remaining data to predict the omitted values. This process is repeated for each data point, and the Q^2 value is computed to indicate how well the model predicts the endogenous constructs. A positive Q^2 value signifies that the model has predictive relevance, while a value close to or below zero suggests limited or no predictive power [91], [92].

Table10 The Predictive Relevance

Variables	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
COPB2	0.339	0.833	0.62	0.921	0.702
COPB3	0.364	1.009	0.807	1.002	0.759
COPB4	0.439	0.787	0.614	0.907	0.687

COPB6	0.391	0.902	0.719	0.98	0.764
COPB8	0.289	0.914	0.725	1.066	0.826

The predictive power of Q^2 was assessed by comparing the PLS-SEM and LM scores for relevant items, following reference [91] and reference [87]. The Q^2 values, ranging from 0.289 to 0.439, exceeded zero, confirming the model's medium predictive power. Most variables (RMSE = 1 out of 3; MAE = 2 out of 3) showed higher error scores in LM compared to PLS-SEM, with COPB8 exhibiting the largest discrepancy in both RMSE (LM = 1.066 vs. PLS-SEM = 0.914) and MAE (LM = 0.826 vs. PLS-SEM = 0.725). These results suggest that while LM tends to yield higher prediction errors, the overall model demonstrates medium predictive power, as evidenced by the positive Q^2 values.

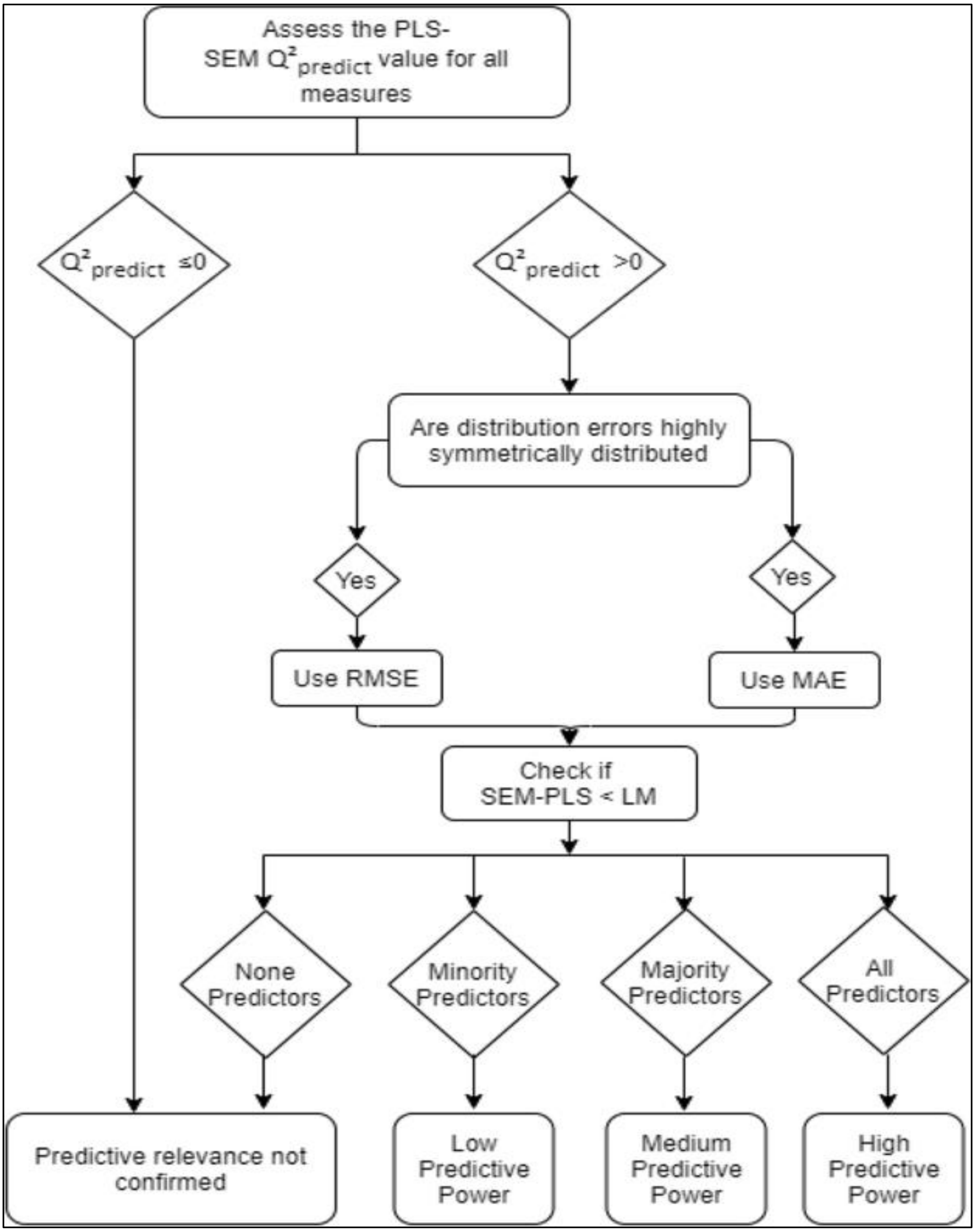

Fig 3 The Model of Predictive Power

FINDINGS AND DISCUSSION

The findings of this study provide valuable insights into the factors influencing Customer Online Purchase Behavior (COPB) in the context of Online Food Delivery (OFD) applications. By employing Partial Least Squares Structural Equation Modeling (PLS-SEM), the results indicate that several constructs from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) significantly predict COPB, while others show no substantial impact. These findings contribute to the understanding of consumer behavior in the OFD industry, which has witnessed substantial growth, particularly in regions like Malaysia, where the market is expected to expand significantly in the coming years.

The results highlight the significant positive influence of Hedonic Motivation (HM), Habit (HB), Trialability (TB), Social Influence (SI), and Price Value (PV) on COPB. Among these, Hedonic Motivation (HM) ($\beta = 0.357$, $p < 0.001$) emerges as the strongest predictor of COPB, which aligns with existing literature emphasizing the psychological and emotional drivers of technology adoption. As noted by researchers like [60], [61], and [64], the enjoyment and pleasure derived from using OFD applications play a pivotal role in shaping consumer behavior. The hedonic value of these platforms, often linked to convenience, aesthetic appeal, and personalized experiences, reinforces the idea that consumers are not solely motivated by functional benefits but also by the enjoyment they derive from using the technology. This aligns with the findings of [65], where Hedonic Motivation (HM) significantly influenced consumer behavior during the COVID-19 pandemic, as individuals sought comfort and pleasure through online platforms. Therefore, hypothesis H_5 is supported for this study.

Similarly, Habit (HB) ($\beta = 0.265$, $p < 0.001$) is another significant determinant of COPB. The role of Habit in technology adoption is well-documented, with studies suggesting that consumers who have prior usage experience are more likely to engage in repeat behavior. This aligns with the UTAUT2 framework, which posits that Habit (HB) reflects automatic behaviors formed through repeated usage, often influencing future adoption and satisfaction [69]. The significant impact of Habit on COPB in this study emphasizes the need for OFD service providers to focus on enhancing customer experience to cultivate long-term usage patterns and retention. Thus, hypothesis H_7 is also supported for this research.

Trialability (TB) ($\beta = 0.204$, $p = 0.001$) also demonstrates a positive influence on COPB, which is consistent with the Diffusion of Innovation Theory. As noted by [72], [73], the ability to trial a product or service before full adoption reduces uncertainty and increases consumer confidence. In the context of OFD applications, trialability can be facilitated through promotional offers, free trials, or introductory discounts, which encourage users to experience the service before making a commitment. This finding is critical for OFD platforms aiming to attract new customers or expand their user base. Consequently, hypothesis H_8 is supported for this extent of this research.

Social Influence (SI) ($\beta = 0.194$, $p = 0.001$) and Price Value (PV) ($\beta = 0.111$, $p = 0.049$) further emphasize the importance of external factors in shaping consumer behavior. Social influence, which refers to the impact of peers, family, or online reviews, has been shown to significantly affect technology adoption [22], [54]. In the case of OFD applications, recommendations from trusted sources or positive reviews play a crucial role in consumer decision-making. Price Value (PV) also emerged as a significant factor, reinforcing the idea that consumers weigh the benefits of using OFD services against the costs, with value-conscious consumers more likely to engage with platforms offering discounts, promotions, and competitive pricing [66]. Hence, both hypothesis H_3 and hypothesis H_6 is supported.

On the other hand, the study reveals that Performance Expectancy (PE) ($\beta = -0.023$, $p = 0.351$), Effort Expectancy (EE) ($\beta = 0.010$, $p = 0.440$), and Facilitating Conditions (FC) ($\beta = -0.069$, $p = 0.138$) do not significantly influence COPB. Therefore, the following hypothesis (H1, H2 and H4) were not supported prior this research.

The non-significance of Performance Expectancy (PE) in this study is surprising given that earlier research has consistently demonstrated its positive influence on users' adoption and continued use of technology [3], [32]. However, the lack of a significant effect in this study can be attributed to a few key factors. First, it is possible that the participants in this research—users of online food delivery (OFD) applications—may no longer prioritize the utilitarian benefits of these platforms once they have become familiar with their offerings. As OFD applications have become widely integrated into daily life, the performance benefits (e.g., time-saving or convenience) might be taken for granted by users. These platforms have become a norm rather than an innovation, which reduces the novelty and perceived performance improvements that users initially sought when first adopting the service [28]. This finding aligns with prior studies suggesting that in mature markets, performance expectancy might play a lesser role in predicting technology usage compared to hedonic or social factors [93], [94].

As for the non-significance of Facilitating Conditions (FC), can also be explained by the increasing ubiquity of the necessary infrastructure to use OFD platforms. In more developed technological environments, such as Malaysia, the essential conditions for using these services, such as internet access, smartphone ownership, and digital payment systems, are widely available [3]. As a result, these facilitating conditions may no longer be perceived as a barrier to usage, as they are generally taken for granted by consumers [32]. This interpretation is consistent with findings from other studies, which found that once the basic infrastructure is sufficiently developed, facilitating conditions lose their predictive power in technology adoption models ([95], [96] Furthermore, because most users of OFD platforms have access to the required technology, the emphasis shifts away from concerns about access or technical support, which diminishes the relevance of Facilitating Conditions in shaping customer behaviour [95].

Last but not least, Effort Expectancy (EE) also showed a marginally significant positive effect, suggesting that although it might play a role in influencing behavior, it is not as influential as other factors such as Social Influence or Hedonic Motivation. This non-significant effect can be explained by the fact that many OFD applications have become highly optimized and user-friendly, reducing the perceived effort required to use them. For example, many users are now familiar with common features such as menu navigation, order tracking, and payment processing, which may have minimized the perceived effort of using these platforms over time [97]. Additionally, prior research has indicated that as technology adoption matures, users may become less sensitive to issues of ease of use, particularly when the platform is intuitive and requires minimal effort to operate [98]. This is consistent with studies suggesting that, in the case of mature digital platforms, Effort Expectancy might have a reduced effect on technology adoption compared to other factors like social influence or the hedonic experience [96], [99].

CONCLUSIONS

In conclusion, the findings of this study contribute to the growing body of literature on online food delivery services by providing empirical evidence on the key drivers of consumer purchase behavior. The results suggest that Hedonic Motivation (HM), Habit (HB), and Trialability (TB) are the primary predictors of COPB, while Performance Expectancy (PE), Effort Expectancy (EE), and Facilitating Conditions (FC) show limited influence. These insights are valuable for OFD service providers seeking to optimize their platforms and marketing strategies to better meet the needs and preferences of their customers. Future research could further explore these relationships across different cultural and demographic contexts to deepen our understanding of the factors driving adoption and usage of OFD applications.

ACKNOWLEDGMENT

I would like to express my deepest gratitude to University Technology Mara (UiTM) Cawangan Selangor Campus Puncak Alam, Faculty of Hotel and Tourism Management, for providing me with the opportunity and resources to conduct this research.

Special thanks to my main supervisor, Dr. Muhammad Izzat bin Zulkifly, whose unwavering guidance, support, and expertise were invaluable throughout this journey. I would also like to extend my sincere appreciation to my co-supervisor, Dr. Zurena@Rena binti Shahril, for her insightful feedback and continuous encouragement.

I am deeply grateful to my parents, whose love, support, and belief in me have been my constant source of motivation. To my family and friends, thank you for your understanding, patience, and encouragement, which have been pivotal in helping me reach this stage.

Finally, I dedicate this work to everyone who has supported and believed in me throughout this academic

endeavour.

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