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Investigating the Mediating Effect of Behavioural Intention to Use in the Relationships between Technology Acceptance Factors and Usage of Online Food Delivery Applications in Sarawak

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Abstract

The current study investigated the mediating of behavioural intention to use in the relationships between technology acceptance factors and usage of online food delivery applications in Sarawak. The framework of this research was drawn from the perspective of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model with two additional constructs, namely trust and risk. The study was based on a sample gathered from users of online food delivery applications in Sarawak. Data were collected using a self-administered online questionnaire. Of the 411 returned questionnaires, 400 questionnaires were valid for analysis. IBM-SPSS Amos 24.0 procedures were utilised to analyse the data and test the hypotheses. This study focused on the significance of all constructs of the proposed conceptual model, and new findings pertaining to these constructs have been highlighted. The findings of the study lead to the conclusion that there are significant relationship was supported (effort expectancy, facilitating condition, hedonic motivation, trust and risk). For the remaining constructs (performance expectancy, social influence, price value and habit) no significant relationship was found. Meanwhile, there is a significant relationship between behavioural intention to use and online food delivery applications usage. Further, behavioural intention to use was found to be a strong mediator for most of the relationships investigated in the theoretical model of this study. The significance of the findings enable to highlight the important factors for promoting online food delivery applications among users in aforesaid context.

Keywords: Technology Acceptance Factors, Behavioural Intention to Use, Online Food Delivery Applications Usage

Introduction

In Malaysia, the increase in the number of food and beverage industry players has also contributed to the usage of online food delivery services in Malaysia (Chai et al., 2019). Online food delivery in the country is available from a wide variety of establishments, including restaurants and food delivery companies (Allah Pitchay et al., 2021; Nayan & Hassan, 2020). Foodpanda is the first food delivery company established in Malaysia, that approximately 75 per cent of Malaysians were in favour of using the Foodpanda food delivery app (Hassan, 2018). Data showed that the Foodpanda Malaysia application in Google Play Store had been download more than 10 million times (Rosli, 2018). This scenario indicates that people are becoming more willing to accept it because of the convenience it offers, especially during a busy day, and the chance to discover more food choices through the application (Allah Pitchay et al., 2021). Traffic congestion, a full-time schedule, and active living are the reasons for using food delivery service applications (Prabowo & Nugroho, 2019). The greatest concentration of food delivery services may be found in major urban areas such as Kuala Lumpur, the Klang Valley, and Johor Bahru (Mat Nayan & Hassan, 2020). According to Yellow Bees (n.d.), there are 12 top food delivery marketplaces in Malaysia. Figure 1 provides a comparison of these food delivery platforms.

Brand	Type	App Installs	Web Order	Coverage	Distance	Own Logistics	Demographics	Service Fees
GrabFood	Super app	100,000,000	Yes	Major cities nationwide	10km	Yes	All	Up to 30%
Foodpanda	Food & grocery delivery	50,000,000	Yes	Major cities nationwide	Depends on restaurants	Yes	All	25-35%
ShopeeFood	Super app	10,000,000	Yes	Klang Valley	N/A	Yes	All	20%
airasia food	Super app	10,000,000	Yes	Klang Valley, Penang, Ipoh	60km	Yes	All	15%
EASI (Hungry)	Food & grocery delivery	500,000	No	Selected cities	N/A	Yes	Chinese	N/A
Bungkusit	Food & parcel delivery	500,000	No	KV, PG, Terengganu, Ipoh, Johor	N/A	Yes	Malay	20%
DeliverEat	Food delivery	100,000	Yes	Penang, Klang Valley	7km	Yes	All	30%
LOLOL	Food & grocery delivery	100,000	Yes	Klang Valley, Melaka, Johor	40km	Yes	Chinese	3%
GemSpot	Table booking & food delivery	100,000	No	Klang Valley	40km	Partner	All	20%
Beep Delivery	Food delivery	50,000	Yes	Klang Valley, Penang, Johor	20km	Hybrid	All	Up to 20%
Tapau	Food delivery	50,000	Yes	Northern Region etc.	N/A	Yes	Malay	N/A
OdaMakan	Food delivery	50,000	Yes	Kelantan & other selected cities	10km	Yes	Malay	20%

Note: Data updated in Sep 2021

Figure 1
Comparison of Food Delivery Platforms in Malaysia in 2021

Problem Statement

The Sarawak government is serious about improving the e-commerce delivery system in the state (Utusan Borneo Online, 2021). Therefore, the development of the digital economy through Sarawak Digital Economy Corporation (SDEC) has taken a further step ahead to ensure that the state keeps up with the technological advancements. The Sarawak Digital Economy Strategy is formulated to help the state achieve a high-income status through digital transformation. However, one of the issues faced by the state is that the public is yet to accept the digital world (Jugah et al., 2022). Different income groups have different levels of acceptance towards the implementation of the Sarawak Digital Economy Strategy. Low-income groups have yet to fully utilise the available digital economy compared to high income groups. It was reported that the household monthly income's poverty range was from RM980 to RM2208, and Sarawak had a very high number of families living in poverty (The Star, 2020).

Moreover, due to underdeveloped infrastructures, Sarawak has continued to face challenges with a lack of a supportive ecosystem such as the availability of local technology, skilled talent, efficient supply chain, attractive incentives, and lower production costs (BusinessToday, 2020). In addition, online fraud crime cases have been on an increasing trend, with the number of cases rising by 92.16 per cent from 1,462 cases in 2020 to 2,816 cases in 2021, as reported by Jabatan Siasatan Jenayah Komersil (JSJK) Sarawak. It is equivalent to an increase in losses to RM7.1 million, in which a loss of RM3 million is attributable to 667 cases involving fraudulent purchases on the internet (e-commerce) platform (Utusan Borneo Online, 2022).

Therefore, this study aimed to examine the relationship between consumers' intention to use and their usage of online food delivery applications as an e-commerce delivery system in the Sarawak context. This is because relatively few studies have investigated the usage of online food delivery applications in the aforesaid context. It is important to examine the factors affecting the intention to use this technology in the food segment (Alalwan, 2020a; Tandon et al., 2021). The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model was adopted as a theoretical foundation that comprehensively captured the factors influencing the technology acceptance of online food delivery applications (Tamilmani et al., 2021). Some studies have empirically proven the existence of significant relationships between technology acceptance factors (performance expectancy, effort expectancy, social influence, facilitating condition, price value, and hedonic motivation) and consumers' behavioural intention to use online food delivery applications (see Gârdan et al., 2021; Alalwan, 2020a; Jasim et al., 2022; Muangmee et al., 2021; Puriwat & Tripopsakul, 2021; Ramos, 2022; Zanetta et al., 2021; Zhao & Bacao, 2020). Substantial research has been done on consumers' usage of online food delivery services. However to date, there is limited research on whether consumers' behavioural intention to use mediates the relationships between technology acceptance factors and online food delivery applications usage. Hence, this study was designed to accomplish the following specific objective:

- To determine the mediating effect of behavioural intention to use in the relationships between technology acceptance factors and usage of online food delivery applications

Literature Review

Performance Expectancy

According to Venkatesh et al (2003, 2012), performance expectancy is the anticipation of a user, in which a person feels that by utilising the system, they would be able to increase their task or professional performance. Many studies have developed and tested the performance expectancy construct through the expanded and extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model in the online food delivery context (see Gunden et al., 2020; Ramos, 2022; Alalwan, 2020a; Allah Pitchay et al., 2021; Palau-Saumell et al., 2019; Lee et al., 2019; Muangmee et al., 2021; Jasim et al., 2022; Zanetta et al., 2021). Their empirical findings showed that performance expectancy was one of the antecedents of the intention to use online food delivery services. This was the situation for as long as the consumers believed that online food delivery applications were effective for searching and simple to use for placing food and beverages orders. Hence, the study hypothesised that

H1: Performance expectancy has a significant influence on the behavioural intention to use online food delivery applications

Effort Expectancy

Effort expectancy can be defined as a system's ease of use, which entails the degree of simplicity pertaining to the functioning of the system (Venkatesh et al., 2003, 2012). Many studies have developed and tested the effort expectancy construct through the expanded and extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model in the online food delivery context (see Gunden et al., 2020a; Ramos, 2022; Alalwan, 2020a; Allah Pitchay et al., 2021; Palau-Saumell et al., 2019; Lee et al., 2019; Muangmee et al., 2021; Jasim et al., 2022; Zanetta et al., 2021). Their empirical findings demonstrated the role of effort expectancy as one of the antecedents of people's intention to use online food delivery. The results also showed that effort expectancy was a strong predictor and had a significant effect on the intention to use online food delivery, as long as the users perceived online food delivery applications as effective and user-friendly for searching and placing orders for food and beverages. Hence, the study hypothesised that:

H2: Effort expectancy has a significant influence on the behavioural intention to use online food delivery applications.

Social Influences

Social influence refers to the extent to which an individual considers the perspectives of other people to be essential in modifying their behaviour towards using a new system by an increased willingness of other people (such as family members, friends, and co-workers) to use a particular technology (Venkatesh et al., 2003). Jasim et al (2022) also investigated the social influence factor in their study and anticipated it to have a significant positive impact on customers' intentions. Their findings showed that social influence had a substantial influence on customers' intentions. This indicates that people may have a greater capacity for motivation if they receive a certain level of encouragement from co-workers, family members, and friends. This encouragement can be provided in various settings, including the workplace, the family home, and social settings. It has the potential to have a substantial impact not only on their awareness of technology but also on their intention in relation to it. Hence, the study hypothesised that

H3: Social influence has a significant influence on the behavioural intention to use online food delivery applications

Facilitating Conditions

According to Venkatesh et al (2003), facilitating condition is defined as the degree to which an individual believes that there is adequate organisational and technical infrastructure to support the use of technology. Researchers in the fields of information technology and digital marketing have concluded that facilitating conditions have a significant influence on customers' intention to use a product and their actual behaviour when using that product (Khalilzadeh et al., 2017; Verkijika, 2018). Zanetta et al (2021) found that the effect of facilitating conditions on continuance intention was significantly stronger in the context of online food delivery in Brazil. They believed that if there was adequate organisational and technical infrastructure to support the use of technology, consumers would have a greater intention to use the technology. Therefore, the intention to continue using technology could be influenced by factors such as the availability of money and time,

as well as access to the internet and cognitive and motor capacities. Hence, the study hypothesised that
H4: Facilitating condition has a significant influence on the behavioural intention to use online food delivery applications

Price Value

Venkatesh et al (2012) defined price value in Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model as the cognitive exchange between the perceived benefits of an application and the monetary cost of using it. This is referred to as the price value equation. When customers believe that the value they receive from using an application is greater than the cost of using it, the price value has a positive influence on their intention to use the application. Previous research has suggested that the use of applications for online meal delivery does not incur any kind of financial cost, as there is no additional fee that must be paid for the installation of a free app (Alalwan, 2020b; Shaw & Sergueeva, 2019). However, customers can obtain significant monetary savings through loyalty programmes or discounts, which are perceived as benefits which considering the demand, signals, and price variations (Koiri et al., 2019; Tomacruz & Flor, 2018). Some of examples such as discount offers, availability of comparative prices, and simplicity of choosing (Jain et al., 2020; Saad, 2021). Hence, the study hypothesised that

H5: Price value has a significant influence on the behavioural intention to use online food delivery applications

Hedonic Motivation

Conceptually, hedonic motivation can be articulated in terms of intrinsic motivations such as playfulness, enjoyment, fun, and pleasure that can be derived from utilising new products, services, and applications; consequently, such feelings of pleasure could be linked to the extent to which the level of innovativeness and novelty in utilising new systems is present in the experience (Van der Heijden, 2004; Venkatesh et al., 2012). Mobile applications are becoming an increasingly significant component of people's lives all over the world. In addition, applications such as mobile food ordering apps (MFOAs) are regarded as being cutting-edge and innovative (Yeo et al., 2017), which may give customers a sense of satisfaction and pleasure when utilising the innovative new software (Okumus et al., 2018; Yeo et al., 2017). Hence, the study hypothesised that:
H6: Hedonic motivation has a significant influence on the behavioural intention to use online food delivery applications

Habit

Limayem et al (2007) defined habit as an individual's propensity to act without a conscious thought as a result of the individual's accumulated learning experience. People are becoming more dependent on their smartphones and have developed a pattern of behaviour regarding the use of the mobile applications that are associated with them. In the context of restaurant searches and/or reservations (MARSR), the findings showed that habit was the most powerful predictor of both intentions to use and actual usage (Palau-Saumell et al., 2019). The authors found that the intention to use a restaurant app became less critical when the habit became stronger, since the probability of using it continuously was much higher. This phenomenon was seen in the significant influence of habit on the utilisation of restaurant searches and/or reservations (MARSR). This finding lends credence to the results of earlier studies conducted on people who used the internet, which discovered habit had a direct effect on technology use but a more moderate impact on intentions to use. Hence, the study hypothesised that

H7: Habit has a significant influence on the behavioural intention to use online food delivery applications

Trust

Notably, Muangmee et al (2021) discovered that perceived trust was among the factors influencing users' intention to use online food delivery. The study provides users and owners of online food delivery applications with the aspects that they should focus on pertaining to the overall technology. Insofar as the enhancement of online food delivery applications and their performance are concerned, it would appear that the appropriateness of technology in terms of its fit, perceived trust, and operational period should be considered. Similarly, Wen et al (2022) demonstrated that perceived trust had a significant influence on consumers' intentions to continue using food delivery apps. Hence, the study hypothesised that:
H8: Trust has a significant influence on the behavioural intention to use online food delivery applications

Risk

Hwang and Choe (2019) investigated the importance of managing perceived risk in the context of drone food delivery (DFD) services. The study found that perceived risk had a positive effect on the intention to use and the willingness to pay more. The study has important theoretical and practical implications for success in developing drone food delivery (DFD) services. In particular, the most important contribution of the study is pertaining to the suggestion to foodservice companies providing drone food delivery (DFD) services on how to reduce the perceived risk of their services. The study by Poon and Tung (2022) found some interesting findings in its investigation of the impacts of perceived risks on consumers' desire and intention to use online food delivery services. Consumers' perception of risk was found to have a negative impact on their intention to use online food delivery services due to a complicated mechanism that influenced their motivation to act in a particular manner. The findings imply that people who use online food delivery services consider a variety of critical risk factors when deciding what motivates them. The fact that consumers have any of these concerns at all demonstrates that their desire and intention to use online food delivery services are being hindered. Consumers have a tendency to be more motivated to engage with online food delivery services if they perceive that there will be minimal adverse effects brought on by the engagement. Therefore, it is up to restaurants and operators of online food delivery to managing and mitigating the risks. Hence, the study hypothesised that:
H9: Risk has a significant influence on the behavioural intention to use online food delivery applications

Behavioural Intention to Use

According to Bhattacherjee (2001); Bhattacherjee and Lin (2015), people's intentions to use a technical product or service are analogous to repeat purchases; however, the acceptance of technology and the continuation of its use are two completely separate concepts, both conceptually and historically. Acceptance occurs during the earliest stages of an individual's experience with a new technology when the person is still unfamiliar with the technology. This is because acceptance is a process that builds on familiarity. In later stages, the significance of other choice variables will become more apparent. Previous studies developed and tested the relationship between behavioural intention to use and use behaviour via the expanded and extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model in the online food delivery context (see Ali et al., 2020; Dat Tran et al., 2021; Luna et al., 2021; Candra et al., 2021; Puriwat & Tripopsakul, 2021; Palau-Saumell et al., 2019; Jasim et al., 2022). Their empirical findings showed the existence of a significant relationship between the behavioural intention to use and online food delivery usage. Hence, the study hypothesised that

H10: Behavioural intention to use has a significant influence on online food delivery applications usage

Behavioural Intention to Use as a Mediator

The significance of a mediation model mainly depends on the design decisions that should be considered before performing any analysis and even before conducting the research. The need for a mediator in a model must be explicitly raised and justified up front by responding to why a mediator is needed and which variable should be considered the mediator (Memon et al., 2018). Therefore, one of the greatest strengths of mediation analysis is in building and refining theory. This is because many theories are based on the results of cross-sectional studies with little or no experimental verification. Therefore, the mediation analysis in a randomised design that is often used in intervention research is ideal for testing theories (MacKinnon et al., 2012). A mediation effect will most probably occur when the relationship between the determining factor and the mediator, as well as the relationship between the mediator and the dependent variable, are established (Memon et al., 2018; Gürbüz & Bayık, 2021; Meule, 2019).

Thus, based on the above discussion has explained the relationships between all the independent variables (performance expectancy, effort expectancy, social influence, facilitating condition, price value, hedonic motivation, habit, trust, and risk) and behavioural intention to use, as well as the relationship between behavioural intention to use and use behaviour in the context of online food delivery. Therefore, this study included behavioural intention to use as a mediator between users' technology acceptance factors (performance expectancy, effort expectancy, social influence, facilitating condition, price value, hedonic motivation, habit, trust, and risk) and online food delivery usage. Hence, the study hypothesised that

H11a: Behavioural intention to use mediates the relationship between performance expectancy and online food delivery applications usage.
H11b: Behavioural intention to use mediates the relationship between effort expectancy and online food delivery applications usage.
H11c: Behavioural intention to use mediates the relationship between social influence and online food delivery applications usage.
H11d: Behavioural intention to use mediates the relationship between facilitating conditions and online food delivery applications usage.
H11e: Behavioural intention to use mediates the relationship between price value and online food delivery applications usage.

H11f: Behavioural intention to use mediates the relationship between hedonic motivation and online food delivery applications usage.
H11g: Behavioural intention to use mediates the relationship between habit and online food delivery applications usage.
H11h: Behavioural intention to use mediates the relationship between trust and online food delivery applications usage.
H11i: Behavioural intention to use mediates the relationship between risk and online food delivery applications usage**.**

Methodology

The sample of this study consisted of online food delivery application users aged 18 years and above in Sarawak. Since the sampling frame was not available, this study used G*Power to perform the power analysis (Faul et al., 2007; Kang, 2021). Power analysis determines the minimum sample size by taking into account the part of the model with the largest number of predictors (Hair et al., 2019; Uttley, 2019). For this study, the parameters' values for the minimum sample size determination were set at f2 = 0.15, power = 0.95, Alpha = 0.05, and predictors = 10. The results from G*Power 3.1.9.7 software indicated that this study required a minimum sample size of 96. The researcher planned to limit the sample to 400 respondents, as a sample larger than 400 respondents would cause Structural Equation Model (SEM) to become sensitive, causing any difference to be detected and the goodness-of-fit measures to exhibit poor fit (Awang et al., 2015). Therefore, the sample size for this study should be in the range between the minimum of 96 and the maximum of 400 responses.

Due to the non-availability of a sampling frame, the convenient sampling technique was used for this study. The technique is useful when the target population is defined in terms of a very broad category. With this sampling technique, any member of the target population who is available at the moment is approached and asked to participate in the research; if the person shows consent, the investigation is done (Alvi, 2016). For the present study, the researcher included those participants who were easy or convenient to approach. The convenient sampling technique was selected because it requires less effort, cost, and time as the sample is quick and easy to approach.

Questionnaires are considered to be one of the most suitable data collection tools for collecting data from large samples (Saunders et al., 2019). The online questionnaire may provide a viable alternative method for carrying out a research plan (Siva et al., n.d.). Besides, it offers a higher response rate (Wu et al., 2022). In this study, the selection of respondents was based on the coverage areas of online food delivery services by Foodpanda and GrabFood. This was because Foodpanda (70.36%) and GrabFood (63.19%) were the popular online food delivery applications among Malaysian online food delivery users due to the user-friendliness of their systems (Tan et al., 2021). Besides, GrabFood was available in Kuching, Miri, Bintulu, and Sibu, while Foodpanda was available in Kuching, Petrajaya, Miri, Sibu, Bintulu, dan Samarahan. Data were collected over a period of 2 months from Sarawak's urban and sub-urban population. The urban and sub-urban population was selected since they had better internet connection and the online food delivery applications were available only in urban and sub-urban areas in Sarawak. During the data collection period, a Google Form link was sent to potential respondents after they were contacted online via messaging applications such as Email, WhatsApp, and Facebook. In total, 400 responses were gathered via this method of sampling for further analysis using IBM-SPSS-AMOS 24.0.

Research Instruments

In this study, the conceptual domains of the constructs were mainly adopted from Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model (Venkatesh et al., 2012), consisting of the constructs of performance expectancy, effort expectancy, social influence, facilitating condition, price value, hedonic motivation, habit, intention to use, and usage, along with two additional constructs comprising trust and risk. All the constructs were adapted in the context of online food delivery applications usage in Sarawak.

After creating a pool of relevant constructs and items from the literature review, a total of 11 constructs (performance expectancy, effort expectancy, social influence, facilitating condition, price value, hedonic motivation, habit, trust, risk, intention to use, and usage) and 48 items were selected. Tables 2 present the number of items and the sources for the constructs.

Table 1
Summary of Items to Measure Each Construct

Construct	No. of items	Source
Performance expectancy	6	(Venkatesh et al., 2003) (Gunden et al., 2020) (Palau-Saumell et al., 2019)
Effort expectancy	6	(Venkatesh et al., 2012) (Palau-Saumell et al., 2019)
Social influence	4	
Facilitating condition	5	
Hedonic motivation	3	
Price value	3	(Venkatesh et al., 2012) (Palau-Saumell et al., 2019) (Lee et al., 2019)
Habit	4	(Venkatesh et al., 2003) (Gunden et al., 2020) (Palau-Saumell et al., 2019)
Behavioural intention to use	4	
Usage	4	(Venkatesh et al., 2003)
Trust	5	(Hamid et al., 2022)
Risk	4	(Yen, 2022)

Results

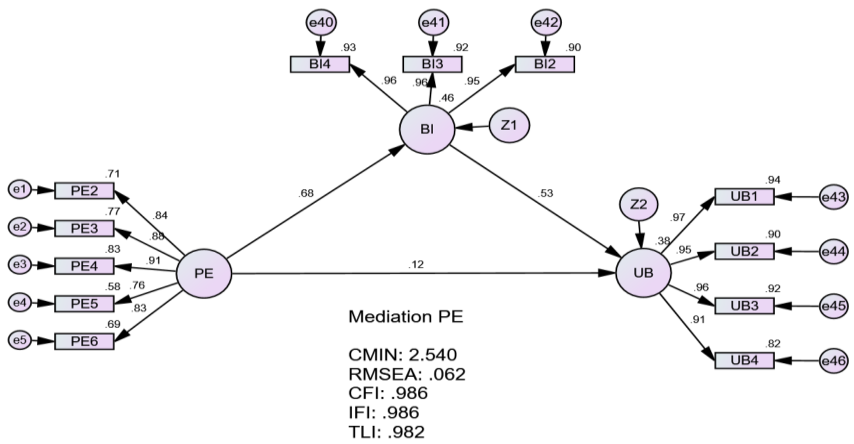
Testing the Direct Effect Hypotheses

The outcomes of the tests on the direct effect hypotheses were determined based on the probability values (*p*-values). A *p*-value of less than .05 indicated that the hypothesis was significant or supported. The value of the regression coefficient showed the effect of an exogenous construct on its corresponding endogenous construct. In this regard, a one-sided arrow represented the causal effect of an exogenous construct on its corresponding endogenous construct (Awang, 2015b; Awang et al., 2018). This study was to examine the relationships between technology acceptance factors and behavioural intention to use, represented by ten hypotheses (H1, H2, H3, H4, H5, H6, H7, H8, and H9). Of these nine hypotheses, the existence of a significant relationship was supported for six hypotheses (H2, H4, H6, H8, H9 and H10). For the remaining four hypotheses (H1, H3, H5, and H7), no significant relationship was found.

Table 2
Summary of Direct Effects

Hypotheses				Estimate	S.E.	C.R.	P	Interpretation
H1	BI	<---	PE	0.18	0.067	2.687	0.007	Not Significant
H2	BI	<---	EE	0.128	0.033	3.909	***	Significant
H3	BI	<---	SF	-0.078	0.052	-1.487	0.137	Not Significant
H4	BI	<---	FC	0.489	0.045	10.92	***	Significant
H5	BI	<---	HM	0.261	0.059	4.431	***	Significant
H6	BI	<---	PV	-0.007	0.047	-0.159	0.873	Not Significant
H7	BI	<---	HA	0.014	0.027	0.526	0.599	Not Significant
H8	BI	<---	PT	0.125	0.038	3.262	0.001	Significant
H9	BI	<---	PR	0.345	0.044	7.767	***	Significant
H10	UB	<---	BI	0.706	0.049	14.453	***	Significant

Testing the Mediation Effect Hypotheses
Performance Expectancy
Figure 2
AMOS Output Showing the Regression Weights Between Constructs (PE-BI-UB)

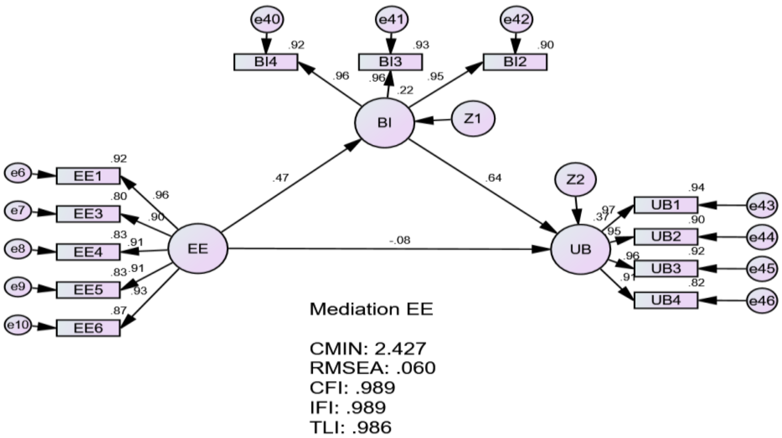


The findings demonstrated the mediating effect of behavioural intention to use on the relationship between performance expectancy and usage. The results for the direct effect of performance expectancy on usage showed a significant effect (b = 0.187, *C.R.* = 2.025, p < .05]. The bootstrapping procedure result confirmed that the direct effect of performance expectancy on behavioural intention to use was significant, which also indicated partial mediation (Awang, 2015; Awang et al., 2018). The result for the indirect effect was also statistically significant (b = 0.36, p < .05). The total effect was 0.04. Since the direct effect was significant (p < .05), the study concluded that behavioural intention to use partially mediated the relationship between performance expectancy and usage.

Table 3
Summary of the Direct and Indirect Effects of Performance Expectancy

Performance Expectancy			Estimate	S.E.	C.R.	P
BI	←-	PE	0.912	0.062	14.59	***
UB	←-	BI	0.605	0.068	8.907	***
UB	←-	PE	0.187	0.092	2.025	0.043
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.12			
Indirect Effect			0.3604			
Total Effect			0.043248			
Decision			Partial Mediation			

Effort Expectancy
Figure 3
AMOS Output Showing the Regression Weights Between Constructs (EE-BI-UB)

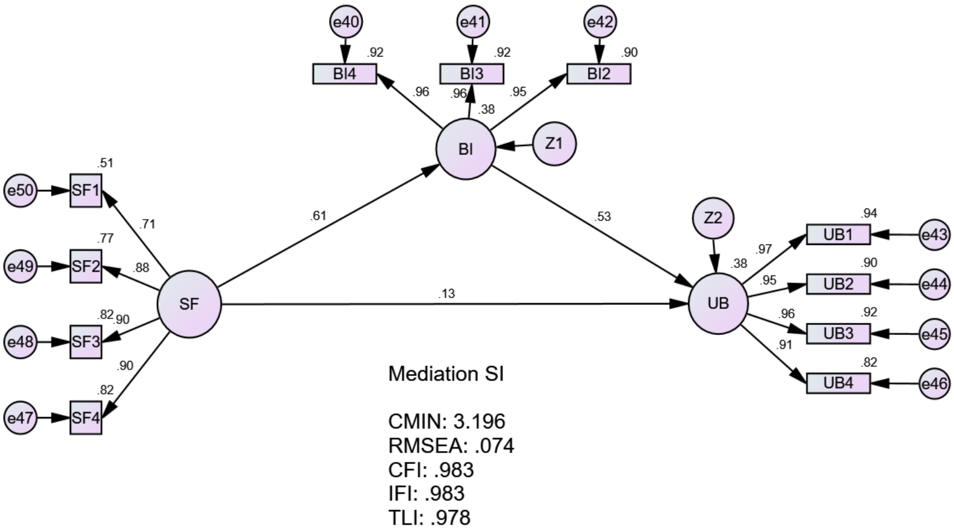


The findings demonstrated the mediating effect of behavioural intention to use on the relationship between effort expectancy and usage. The results for the direct effect of effort expectancy on usage showed that the effect was not significant ($b = -0.102$, $C.R. = -1.62$, $p > .05$). The bootstrapping procedure result confirmed that the direct effect of effort expectancy on behavioural intention to use was not significant, which also indicated full mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant ($b = 0.30$, $p <. 05$). The total effect was 0.22. Since the direct effect was not significant ($p > .05$), the study concluded that behavioural intention to use fully mediated the relationship between effort expectancy and usage.

Table 4
Summary of the Direct and Indirect Effects of Effort Expectancy

Effort Expectancy			**Estimate**	**S.E.**	**C.R.**	**P**
BI	<---	EE	0.539	0.054	9.969	***
UB	<---	BI	0.741	0.056	13.282	***
UB	<---	EE	-0.102	0.063	-1.62	0.105
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			-0.08			
Indirect Effect			0.3008			
Total Effect			0.2208			
Decision			Full Mediation			

Social Influence
Figure 4
AMOS Output Showing the Regression Weights Between Constructs (SF-BI-UB)

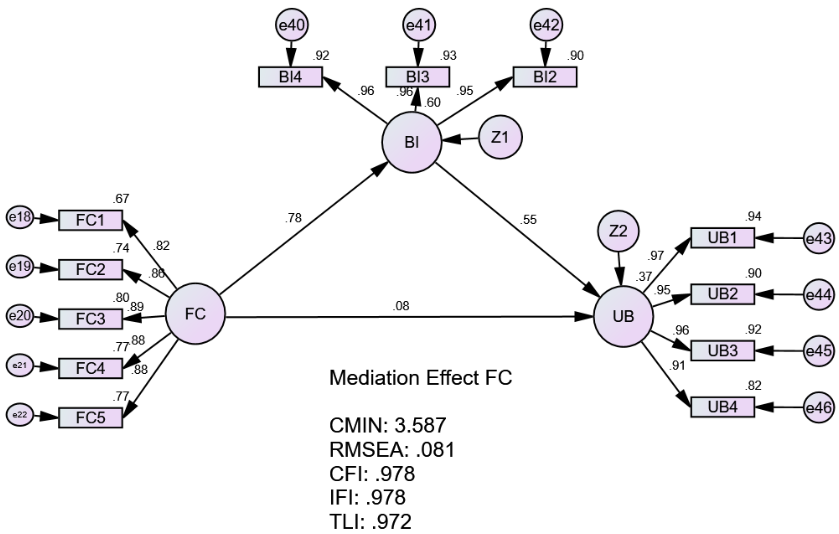


The findings demonstrated the mediating effect of behavioural intention to use on the relationship between social influence and usage. The results for the direct effect of social influence on usage showed a significant effect (b = 0.152, *C.R.* = 2.397, $p < .05$). The bootstrapping procedure result confirmed that the direct effect of social influence on behavioural intention to use was significant, which also indicated partial mediation (Awang, 2015; Awang et al., 2018). The result for the indirect effect was also statistically significant (b = 0.32, $p < .05$). The total effect was 0.45. Since the direct effect was significant ($p < .05$), the study concluded that behavioural intention to use partially mediated the relationship between social influence and usage.

Table 5
Summary of the Direct and Indirect effects of Social Influence

Social Influence			Estimate	S.E.	C.R.	P
BI	←-	SF	0.614	0.045	13.504	***
UB	←-	BI	0.606	0.063	9.673	***
UB	←-	SF	0.152	0.063	2.397	0.017
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.13			
Indirect Effect			0.3233			
Total Effect			0.4533			
Decision			Partial Mediator			

Facilitating Condition
Figure 5
AMOS Output Showing the Regression Weights between Constructs (FC-BI-UB)



The findings demonstrated the mediating effect of behavioural intention on the relationship between facilitating condition and usage. The results for the direct effect of facilitating condition on usage showed that the effect was not significant (b = 0.108, *C.R.* = 1.079, $p > .05$]. The bootstrapping procedure result confirmed that the direct effect of facilitating condition on behavioural intention to use was not significant, which also indicated full mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant (b = 0.429, $p < .05$). The total effect was 0.59. Since the direct effect was insignificant ($p > .05$), the study concluded that behavioural intention to use fully mediated the relationship between facilitating condition and usage.

Table 6
Summary of the Direct and Indirect Effects of Facilitating Condition

Facilitating Condition			**Estimate**	**S.E.**	**C.R.**	**P**
BI	<---	FC	0.948	0.051	18.621	***
UB	<---	BI	0.631	0.081	7.762	***
UB	<---	FC	0.108	0.1	1.079	0.281
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.08			
Indirect Effect			0.429			
Total Effect			0.509			
Decision			Full Mediator			

Price Value

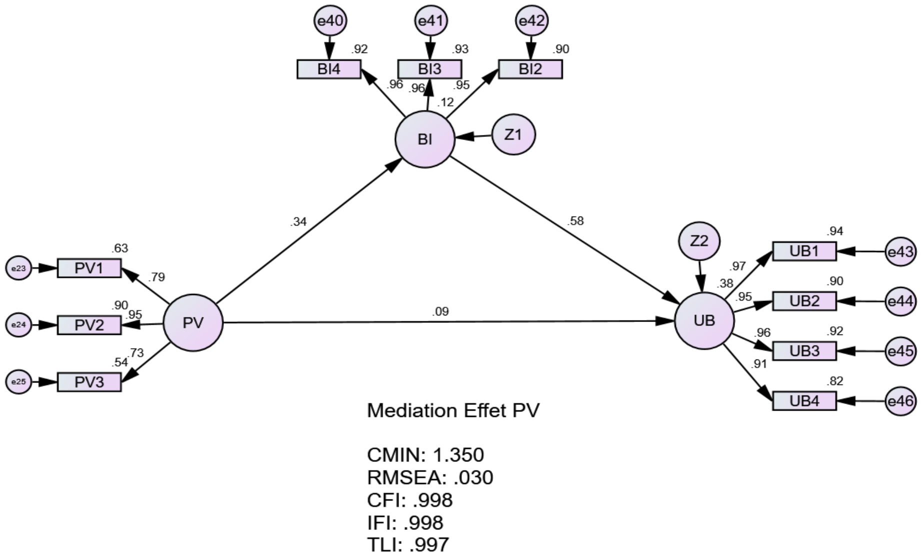


Figure 6
AMOS Output Showing the Regression Weights Between Constructs (PV-BI-UB)

The findings demonstrated the mediating effect of behavioural intention on the relationship between price value and usage. The results for the direct effect of price value on usage showed that the effect was significant (b = 0.162, *C.R.* = 2.027, $p < .05$). The bootstrapping procedure result confirmed that the direct effect of price value on behavioural intention to use was not significant, which also indicated partial mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant (b = 0.1972, $p < .05$). The total effect was 0.2872. Since the direct effect was significant ($p < .05$), the study concluded that behavioural intention to use partially mediated the relationship between price value and usage.

Table 7
Summary of the Direct and Indirect Effects of Price Value

Price Value			Estimate	S.E.	C.R.	P
BI	<---	PV	0.522	0.08	6.502	***
UB	<---	BI	0.664	0.052	12.729	***
UB	<---	PV	0.162	0.08	2.027	0.043
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.090			
Indirect Effect			0.1972			
Total Effect			0.2872			
Decision			Partial Mediator			

Hedonic Motivation

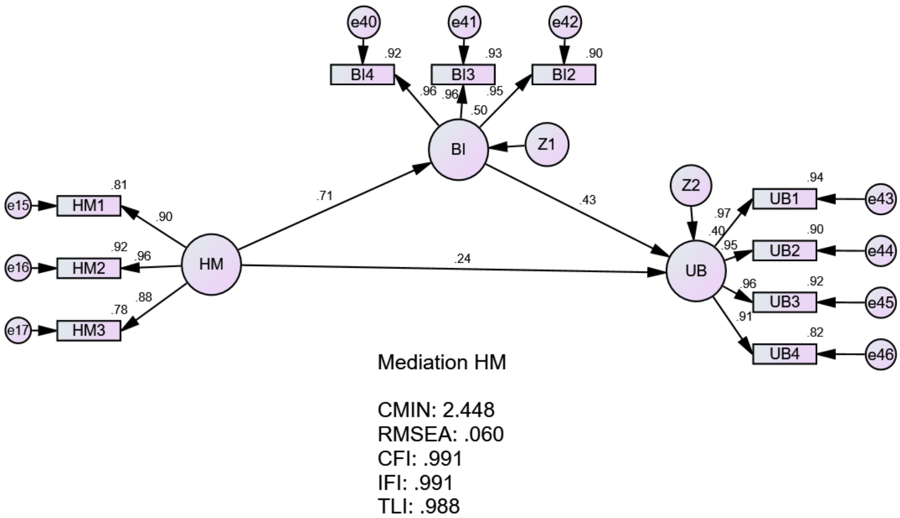


Figure 7
AMOS Output Showing the Regression Weights Between Constructs (HM-BI-UB)

The findings demonstrated the mediating effect of behavioural intention on the relationship between hedonic motivation and usage. The results for the direct effect of hedonic motivation on usage showed a significant effect (b = 0.323, *C.R.* = 4.067, $p < .05$). The bootstrapping procedure result confirmed that the direct effect of hedonic motivation on behavioural intention to use was significant, which also indicated partial mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant (b = 0.3053, $p < .05$). The total effect was 0.5453. Since the direct effect was significant ($p < .05$), the study concluded that behavioural intention to use partially mediated the relationship between hedonic motivation and usage.

Table 8
Summary of the Direct and Indirect Effects of Hedonic Motivation

Hedonic Motivation			**Estimate**	**S.E.**	**C.R.**	**P**
BI	<---	HM	0.808	0.049	16.356	***
UB	<---	BI	0.5	0.069	7.267	***
UB	<---	HM	0.323	0.08	4.06	***
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.24			
Indirect Effect			0.3053			
Total Effect			0.5453			
Decision			Partial mediator			

Habit

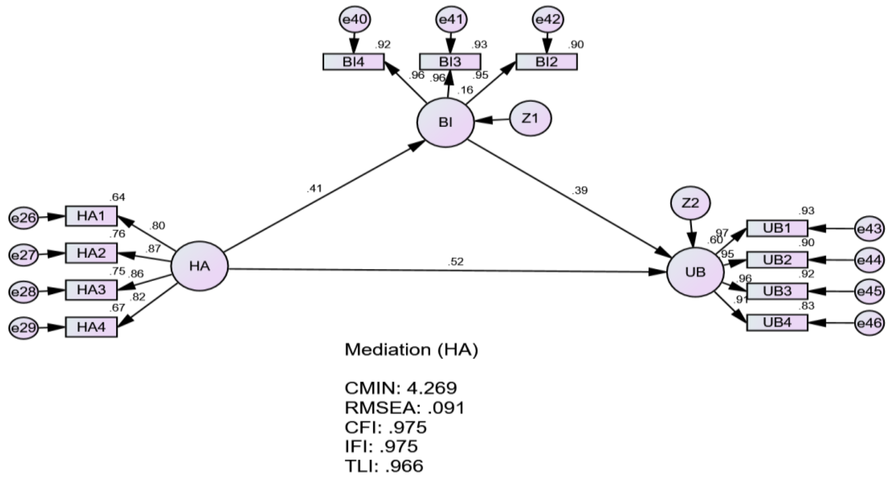


Figure 8
AMOS Output Showing the Regression Weights Between Constructs (HA-BI-UB)

The findings demonstrated the mediating effect of behavioural intention on the relationship between habit and usage. The results for the direct effect of habit on usage showed a significant effect (b = 0.477, *C.R.* = 12.364, $p < .05$). The bootstrapping procedure result confirmed that the direct effect of habit on behavioural intention to use was significant, which also indicated partial mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant (b = 0.1599, $p < .05$). The total effect was 0.6799. Since the direct effect was significant ($p < .05$), the study concluded that behavioural intention to use partially mediated the relationship between habit and usage.

Table 9
Summary of the Direct and Indirect Effects of Habit

Habit			Estimate	S.E.	C.R.	P
BI	<---	HA	0.32	0.04	7.975	***
UB	<---	BI	0.453	0.045	10.17	***
UB	<---	HA	0.477	0.039	12.364	***
P-value Unstandardized Indirect Effect			0.01			
Direct Effect			0.52			
Indirect Effect			0.1599			
Total Effect			0.6799			
Decision			Partial mediator			

Trust

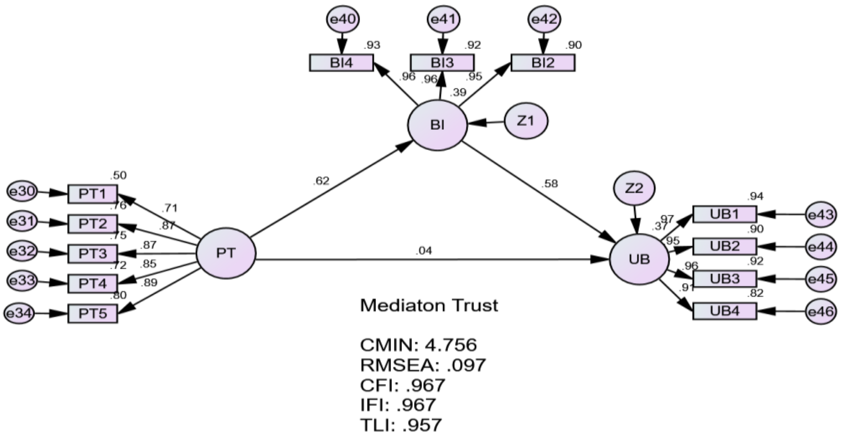


Figure 9
AMOS Output Showing the Regression Weights Between Constructs (PT-BI-UB)

The findings demonstrated the mediating effect of behavioural intention on the relationship between trust and usage. The results for the direct effect of trust on usage showed that the effect was not significant (b = 0.047, *C.R.* = 0.707, $p > .05$). The bootstrapping procedure result confirmed that the direct effect of trust on behavioural intention to use was not significant, which also indicated full mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant (b = 0.3596, $p < .05$). The total effect was 0.3996. Since the direct effect was not significant (p >. 05), the study concluded that behavioural intention to use fully mediated the relationship between trust and usage.

Table 10
Summary of the Direct and Indirect Effects of Trust

Habit			**Estimate**	**S.E.**	**C.R.**	**P**
BI	<---	PT	0.641	0.047	13.77	***
UB	<---	BI	0.67	0.064	10.478	***
UB	<---	PT	0.047	0.066	0.707	0.48
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.04			
Indirect Effect			0.3596			
Total Effect			0.3996			
Decision			Full Mediation			

Risk

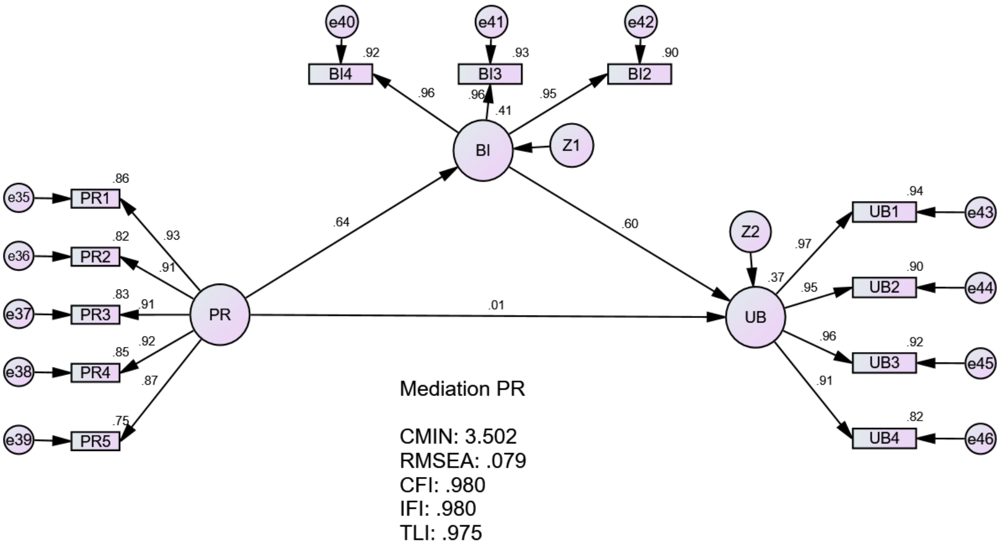


Figure 10
AMOS Output Showing the Regression Weights Between Constructs (PR-BI-UB)

The findings demonstrated the mediating effect of behavioural intention on the relationship between risk and usage. The results for the direct effect of risk on usage showed a not significant effect (*b* = 0.013, *C.R.* = 0.143, *p* > .05). The bootstrapping procedure result confirmed that the direct effect of risk on behavioural intention to use was significant, which also indicated partial mediation (Awang, 2015; Awang et al., 2018). Further, the result for the indirect effect was statistically significant (*b* = 0.384, *p* < .05). The total effect was 0.394. Since the direct effect was significant (*p* > .05), the study concluded that behavioural intention to use fully mediated the relationship between risk and usage.

Table 11
Summary of the Direct and Indirect Effects of Risk

Risk			Estimate	S.E.	C.R.	P
BI	<---	PR	0.903	0.064	14.057	***
UB	<---	BI	0.695	0.065	10.756	***
UB	<---	PR	0.013	0.091	0.143	0.887
P-value Unstandardized Indirect Effect			0.002			
Direct Effect			0.01			
Indirect Effect			0.384			
Total Effect			0.394			
Decision			Full Mediator			

Summary of Mediation Effects
Table 12
Summary of Mediation Effects

Exogenous	Mediator	Endogenous	Results	Type of Mediation
Performance expectancy	Intention To Use	Usage	Yes	Partial mediation
Effort expectancy	Intention To Use	Usage	Yes	Full mediation
Social influence	Intention To Use	Usage	Yes	Partial mediation
Facilitating condition	Intention To Use	Usage	Yes	Full mediation
Price value	Intention To Use	Usage	Yes	Partial mediation
Hedonic motivation	Intention To Use	Usage	Yes	Partial mediation
Habit	Intention To Use	Usage	Yes	Partial mediation
Trust	Intention To Use	Usage	Yes	Full mediation
Risk	Intention To Use	Usage	Yes	Full mediation

Findings and Conclusion

This study was the first endeavour to research the links between technology acceptance factors, behavioural intention to use, and usage of online food delivery applications simultaneously among the users in Sarawak by using SEM. Additionally, to the best of the researcher’s knowledge, no studies have examined the intervening role of behavioural intention to use in the links between technology acceptance factors and usage of online food delivery applications.

Therefore, this current examination connotes the importance of behavioural intention to use as an intervening factor in the links between technology acceptance factors and usage of online food delivery applications. This examination filled the gaps in past investigations on online food delivery use behaviour that reported, based on their empirical findings, the existence of significant relationships between users’ technology acceptance factors (performance expectancy, effort expectancy, social influence, facilitating condition, price value, hedonic motivation, habit, trust, and risk) and behavioural intention to use online food delivery applications (see Gârdan et al., 2021; Alalwan, 2020a; Jasim et al., 2022; Karulkar et al., n.d.; Lee et al., 2019; Muangmee et al., 2021; Palau-Saumell et al., 2019; Puriwat & Tripopsakul, 2021; Ramos, 2022; Zanetta et al., 2021; Zhao & Bacao, 2020). However to date, there is no known study that has discussed the mediating role of behavioural intention to use in the relationships between users' technology acceptance factors (performance expectancy, effort expectancy, social influence, facilitating condition, price value, hedonic motivation, habit, trust, and risk) and online food delivery applications usage.

Most definitely, this study's model was created to determine the relationships between technology acceptance factors, behavioural intention to use, and usage of online food delivery applications, particularly among the users in Sarawak. The outcome has added to new discoveries regarding the intervening role of behavioural intention to use, which has never been tested before. Finally, the model was tested among users in Sarawak for the first time. For these reasons, this investigation fills the gaps in literature.

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