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Factors Influencing Bingobox Technology Adoption on Consumers' Behavioral Intentions in Malaysia Post-COVID-19

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Abstract

China introduced its pioneering concept of human-free and cashless convenience shops, Bingobox, into the Malaysian market. This innovative retail model allows customers to shop independently, without the assistance of store employees, requiring only the scan of a QR code for access and automatic registration of purchases. Given that this technological system is relatively new to users in Malaysia, the motivation behind this study is to understand the challenges and opportunities presented by this novel retail concept, which has the potential to significantly transform consumer behavior and retail practices in the country. To achieve this, the study aimed to investigate the factors influencing the adoption of Bingobox technology in relation to consumers' behavioral intentions in Malaysia, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT2) model. The research questions were designed to identify the factors that statistically significantly affect consumer behavioral intentions. The modified UTAUT2 model comprises seven independent variables: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Hedonic Motivation, Price Value, and Habit. Data was collected through a questionnaire distributed to 150 targeted respondents via URLs or links to Google Forms, disseminated through platforms such as WhatsApp, Telegram, Facebook, and other network-based applications. Analysis was conducted using SPSS for coding and SmartPLS 3.0 for performing Partial Least Squares Structural Equation Modeling (PLS-SEM) path coefficient analysis. The findings revealed that all seven independent variables have significant relationships with the dependent variable, providing valuable insights for practitioners and policymakers in leveraging technology for sustainable business practices. This study contributes to a deeper understanding of the factors driving the adoption of innovative retail technologies in Malaysia, offering guidance for businesses and policymakers in effectively implementing and promoting new technological solutions.

Keywords: BingoBox, UTAUT 2, Technology Adoption.

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Introduction

The checkout process often frustrates shoppers, prompting companies like BingoBox to introduce cashierless stores using Internet of Things (IoT) technology to streamline the experience. The launch of the first IoT-enabled retail facilities, including JD.id's unmanned shop in Indonesia and BingoBox in Kuala Lumpur, marks a growing trend in Southeast Asia. BingoBox, in partnership with Scientific Retail Sdn. Bhd, stands out with over 400 stores in China and now expanding in Malaysia, providing an alternative to traditional checkout systems (Heng Hong 2018). This model not only enhances efficiency but also leverages advanced technologies like RFID tags and QR codes for better product identification and customer experience. The adoption of such technologies reflects the broader movement towards Industry 4.0, characterized by smart systems and data integration. The COVID-19 pandemic has accelerated the need for such innovations, as seen in Malaysia's retail sector, which faced significant challenges and closures during the Movement Control Order (MCO) period.

BingoBox stores allow customers to pick and bag products without a salesperson, using cashless payment methods like WeChat and Alipay. This system includes advanced technologies such as AI, facilitating a seamless shopping experience with features like code scanning and facial recognition. Despite the convenience, some customers are resistant due to privacy concerns or changes in shopping habits (Shishah & Alhelaly, 2021; Soodan & Rana, 2020). The COVID-19 pandemic has further accelerated the adoption of these technologies, as contactless payment solutions became more crucial (Sarmah et al., 2021). In Malaysia, where BingoBox is relatively new, awareness and adoption are still limited, highlighting the need for better marketing and education (Park & Zhang, 2021).

This study applies the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) to explore factors influencing purchase behavior, specifically focusing on BingoBox technology adoption in Malaysia. The research uses SmartPLS 3.0 software to employ partial least squares structural equation modeling (PLS-SEM), allowing for the estimation of complex relationships between latent variables. Quantitative data analysis, including hypothesis testing, is conducted to assess the significance of theoretical factors identified through the questionnaire.

Literature Review and Hypothesis Development

Overview of Bingobox Technology

Bingobox, a pioneering Chinese company in automated retail, stands out with its advanced technology and innovative store model. Established by Auchan, an affiliate of Sun Art Retail Group Ltd., Bingobox introduced its first cashless convenience store in Shanghai’s Yangpu area in June 2017. The store allows customers to shop independently without store staff by using a Tencent app, WeChat. Shoppers scan a QR code to enter the store, and items are automatically tallied at checkout as they scan a second QR code. The store also employs facial recognition technology to ensure that only authorized individuals enter and that their purchases are valid. In 2018, Bingobox's humanless retail technology expanded to Malaysia through a joint venture, introducing unmanned convenience stores at Shell Tezz Enterprise. This innovation allows for 24-hour access and cashless payments, enhancing customer convenience and satisfaction at Shell Select stores.
The technology behind Bingobox includes several key components:

- **Facial Recognition**: Visionify predicts that facial recognition technology will increasingly be used for identity verification by analyzing facial features. It uses biometric data and real-time imaging to compare against databases, providing a secure and efficient method for user identification.

- **Artificial Intelligence (AI)**: Bingobox utilizes AI and machine learning to enhance store operations. AI enables machines to perform cognitive tasks such as learning and problem-solving, which are essential for the seamless operation of unmanned stores. Although AI technology is relatively new and its patenting process is complex, it plays a crucial role in Bingobox's technological infrastructure.

- **Theft Prevention**: Retail theft prevention is critical for Bingobox and other retailers. Techniques include RFID tags, which are used to monitor inventory and prevent theft, and Bluetooth padlocks for securing expensive equipment. These technologies help ensure that merchandise is protected and only accessible after payment.

Overall, Bingobox's integration of advanced technologies such as facial recognition, AI, and theft prevention systems represents a significant advancement in automated retail. Its successful implementation in China and expansion to Malaysia highlight its role as a leader in the future of retail technology (Murugiah, 2018; Visionify, 2021; SafetyCulture, 2022).

Bingobox Mobile Payment Method

Over 500 BingoBox flat-pack stores have already opened in the United States, Taiwan, South Korea, and Malaysia, with plans for further development in Japan and Australia. In compared to 7-Eleven and Tesco Express, a typical BingoBox site is 160 square feet, making it easier to identify appropriate locations, lowering overheads, and allowing for high sales volumes. Customers access the establishments by scanning a QR code with their phone's BingoBox app, then placing their items in a scanner and paying using WeChat, Alipay, or another local payment option. They may also pay in cash (Retail Insight Network, 2019). Boost and Scientific Retail cooperated to provide a smooth mobile payment experience for customers. Boost's vice president of sales and marketing, Chris Tiffin, stated, "We are pleased to collaborate with Scientific Retail to build an integrated payment solution that works flawlessly with Bingobox Retail Technology." In our pursuit of digitising cash, we've always sought to make things easier for our three million customers, and this relationship is another another illustration of that effort: With the integration of Bingobox Retail Technology, customers will just have to use one mobile app to make purchases and pay. Make a cashless purchase using the Boost eWallet App. Pay by scanning a QR code at one of Boost's partner sites or by providing a unique QR code to a merchant.

Overview of UTAUT 2

In the late nineteenth century, information technology (IT) started to recognise the need of user acceptance surveys. The user's acceptance of technology, regardless of how sophisticated it is, was a prerequisite for its use and recognition of its hidden value. IT acceptability issues have been investigated utilising ideas such as the diffusion of innovation theory, PC model use, and the theory of social cognition. The most successful and renowned theories in the IT adoption family are the Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and UTAUT. While the second iteration of the Unified Theory of Acceptance and Use of Technology (UTAUT), which incorporates members of the IT adoption theories, is a step forward from the first.

The Background of Theory of Reasonable Action (TRA)

Theory of Reasoned Action (TRA) was proposed by Fishbein and Ajzen in 1975 based on social psychology (Ajzen & Fishbein, 1975). According to the research, prediction on individuals' behaviour can be formed based on the measurement of an individual's intention in conducting events which further extended to behavioural intention (BI). Behavioural Intention can be identified through the attitude and subjective norm concerning the behaviour in question by an individual. Definition of attitude can be determined with the individual's belief with subjective probability provided that after behavioural action will have a given consequence. Subjective norm can be impressed as a perception of an individual influenced by social pressure from other people who are important to him for individual to exercise in performing the behaviour and their motivation in complying with the view of those people. Based on previous studies, forming intention under the subjective norm's influence will be proved to be feebler than the affection of attitude.

Subjective norms and people's desire to develop them are not linked, according to recent research. As a potential explanation for inconsistencies, it is feasible that the information component which contains the variables is already included inside the desirability of executing a behaviour variable. The most cited flaw in the theory of planned behaviour is the poor connection between behavioural intention and subjective standards. It was hypothesised, according to the theory's creator, that a person's mood and sense of behavioural control may have a significant impact on his or her aim. As a result of this, the association between intents and normative views is shown to be very low (Armitage & Conner, 2001).

The Background of Technology Acceptance Model (TAM)

Davis's Technology Acceptance Model (TAM), an extension of the Theory of Reasoned Action (TRA), examines how perceived ease of use and perceived usefulness influence users' intentions and behaviors toward adopting new information systems (Davis, 1986). TAM posits that a system's perceived ease of use and perceived usefulness significantly affect users' attitudes and their intention to use the system. Perceived usefulness (PU) refers to the belief that using a system will enhance job performance, while perceived ease of use (PEOU) denotes how effortless the system is to use, which can impact users' attitudes and adoption behavior. TAM was further expanded into TAM 2, which integrates organizational and social elements such as subjective norms, image, output quality, and job relevance. TAM 2 incorporates additional factors that affect perceived usefulness and usage intentions, including: (1) Voluntariness: The degree to which users perceive adoption as optional, (2) Image: The extent to which using the system is perceived to improve one's social status, (3) Job Relevance: How well the system fits with the user's job tasks, (4) Quality of Output: The user's impression of the system's capability to perform tasks and (5) Result Demonstrability: The visibility and tangibility of the system's outcomes, which affects its perceived usability.

Despite its theoretical advancements, TAM and TAM 2 have faced criticism. Issues include limited heuristic usefulness, weak explanatory and predictive power, and a focus that may overlook critical social processes and practical aspects of information system implementation

(Benbasat & Barki, 2007). Critics argue that TAM's emphasis on perceived usefulness and ease of use may overshadow other important factors, such as structural constraints and costs, and may not fully account for the social implications of technology adoption. In summary, while TAM provides a foundational framework for understanding technology acceptance, it has been critiqued for its limitations and the need for adaptation to reflect evolving IT environments and broader social influences on technology use.

The Background of Theory of Planned Behaviour (TPB)
The influence of control variables is not considered in TRA. TRA assumes that the user will have complete control over the type of technology adopted and that behaviour will not be influenced by aptitude or external support. Since Ajzen and others identified the issue, modifications to TRA have resulted in the proposed Theory of Planned Behaviour (TPB) (Ajzen & Madden, 1986). An additional construct is perceived behaviour control in accounting situations in which an individual lacks substantial control over the targeted behaviour (Ajzen, 1991). Individual behaviour can be explained by behavioural intention, which is influenced by subjective norms, attitude, and perceived behavioural control. Attitude is an individual's assessment of the performance impact of a given behaviour. Subjective norms may be defined in TAM as an individual's perceptions of other people's opinions on whether an individual should perform a specific behaviour. TPB defined perceived behavioural control as an individual's sense of the existence of the essential resources or opportunities for exhibiting a behaviour. Perceived behavioural control developed from Bandura's self-efficacy theory (SET), which was extended from social cognitive theory (Bandura, 1977). According to current research, expectations such as performance, motivation, and emotions of frustration linked with repeated failures might impact the effect and behavioural response. Expectations may be divided into two types: self-efficacy and outcome expectation. Self-efficacy is defined as the conviction that one can effectively execute the behaviour necessary to achieve results. While outcome expectancy refers to a person's estimate that certain outcomes will be led by a given behaviour. Self-efficacy is the most important premise for behavioural change because it identifies the initiation of coping behaviour. Individuals' behaviour is influenced by their confidence in their ability to perform behaviour.

The contribution of SET to various relationships between beliefs, attitudes, intentions, and behaviour has been given, and it is widely applied to health-related fields such as physical activity and mental health in preadolescents and exercise. TPB's strengths include the ability to explain people's non-volitional behaviour, whereas TRA cannot. The proposed TPB has the variable addition of perceived behavioural control grants it an ability in interpreting the relationship between behavioural intention and actual behaviour. TPB was found to be more effective than TRA in predicting health-related behavioural intention in studies. TPB has been shown to be capable of predicting intention in health-related fields such as condom use, leisure, exercise, and diet. Furthermore, TPB performs the same function as TRA in explaining an individual's social behaviour while taking social norms into account as an important variable. Previous research on these models, such as TRA, TAM, and TPB, has been significant to the field of information technology adoption theories, generating discussions and debates. Hoewver, the theories were still not perfect. Even though the acceptance factors of each theory have different terminologies, the concepts are the same. Because of the complexities of behaviour and the limitations of research, these theories are unlikely to cover most factors.

The Background of Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. established the UTAUT, or Unified Theory of Acceptance and Use of Technology, in 2003 after assessing the eight most prominent theories on IT adoption (Venkatesh et al., 2003). Adjusted R2 for the UTAUT was 70 percent bigger than that of the TAM and TPB models, which were evaluated with just 30 percent of the dependent variable variation. UTAUT believes that elements like performance expectations, effort expectations, social influence, and enabling situations all play a part in determining human behaviour. Utilizing TAM considerably improves one's work performance to the extent that one feels using the system would have a direct link to the value placed on TAM by the user. Additionally, the degree to which one expects that utilising the supported technology will make the work simpler is defined as "effort expectation." One may define social impact as a person's belief in the significance of others, and this new approach could help measure that belief. Whether or not one has faith in the organisation and its technological infrastructure to give the present assistance needed to operate the system is referred to as the "enabling condition."

Furthermore, from the standpoint of social psychology, UTAUT has included moderating characteristics such as age, gender, usage experience, and voluntariness of use. These moderators have the ability to remedy the inconsistencies and lack of explanation produced by earlier models. Furthermore, they may explain the behavioural disparities between various groups of individuals. The responsibilities of moderators are crucial in the study of information technology adoption or ecommerce. UTAUT was used to explore the attitudes of 243 respondents living in northern Finland towards mobile services and technology; the findings revealed that consumer perceptions are influenced by familiarity with devices and user abilities (Koivimäki, Ristola, A, & Kesti, M, 2008).

There are considerable limitations to the UTAUT paradigm not with standing its efficacy in explaining user adoption of IT. At least eight independent variables for predicting behaviour have been added to the existing model, which comprises 41 unique elements for determining intentions and at least eight independent variables for predicting behaviour (Bagozzi & R.P., 2007). There are four primary moderating elements required for a high R2 in UTAUT compared to TAM and TAM2. The proposed UTAUT makes grouping and labelling of items and structures challenging since a variety of unrelated aspects were combined to express a single psychometric notion. UTAU. Several studies have shown that the modifiers used to get high R2 are unimportant and unworkable when trying to understand how organisations embrace new technologies. Initial screening techniques may be used to achieve great predictive power in demonstrations.

The Extension of UTAUT

To overcome the inadequacies of the previous model, Venkatesh et al. have proposed a new model, UTAUT 2, (Venkatesh et al., 2012). Age, gender, experience, and individual characteristics all have an effect on a person's behavioural intention, as do factors like hedonic incentive, price value, and habit. Studies on the uptake of mobile health technology, for example, have employed UTAUT 2 extensively (Duarte & José Carlos Pinho, 2019). PLS-SEM and fuzzy set comparison analysis were used to investigate the number of causative factors that contribute to mHealth uptake. As a result, they concluded that the study's UTAUT2 framework was limited by the lack of characteristics such as healthcare literacy and healthcare status, which necessitated a cautionary note on the sample size. By adjusting the variables' size, this issue may be remedied.

The results showed that all the significant constructs in the model are usable to both gender groups an educational level. Insignificant moderating effects may find as gender and educational level when applying to the certain target market suchas university students. The targeted respondents have known in having high educational level, which could show that the educational level as less power to affect the result of study. The situation could be overcome by testing different moderating
effect which was the socioeconomic status that will be discovered by this study.

The Factor Of Bingobox Technology Adoption Towards Consumers Behavioral Intention
In this study, the researcher had made an integration of two models – TAM and UTAUT 2 in order to identify the factor of bingobox technology adoption towards consumers behavioral intention in malaysia during epidemic of covid-19. Besides, apart from the variables derived from TAM and UTAUT 2, the other independent variable for instance compatibility also considered as a significant measurement of the factor of bingobox technology adoption (Misirlis & Vlachopoulou, 2018).

Performance Expectancy
When it comes to a person's performance expectations, the system is described as how much they feel it can assist them in achieving at work (Shin, 2009). According to Compeau & Higgins (1995), the theoretical foundations of this variable include the technological acceptance model, extrinsic motivation, job fit, relative benefit, and outcome expectancies. Performance expectations are influenced by various factors, including intrinsic drive, perceived utility, and job fit (Shin, 2009). Performance expectation was shown to be the most significant predictor of the intention to use the target technology in each of the models studied. An optimistic outlook, performance expectations, social influence, and favorable conditions significantly impact an individual's decision to file electronically (Schaupp et al., 2010). The amount of IT adoption and use in CHCs was influenced by factors such as performance expectations, effort, social influence, and the level of voluntariness (Kijsanayotin et al., 2009). User adoption is strongly influenced by factors such as performance expectations, task technology fit, social impact, and enabling circumstances. Furthermore, we found that task technology fit significantly impacts performance expectations. There are two factors influencing consumers' behavioral intentions: (1) how much effort they anticipate from their transactions and (2) how innovative they are. Another finding from Martín and Herrero (2012) is that innovativeness moderates the relationship between performance expectations and BingoBox technology behavioral intentions.

H1: There is a positive relationship between performance expectancy towards bingobox technology adoption consumers behavioral intention in malaysia during epidemic of Covid-19.

Effort Expectancy
In the context of the Unified Theory of Acceptance and Use of Technology (UTAUT), effort expectation refers to how easily users perceive a system can be used. This concept aligns with perceived ease of use from Venkatesh et al.'s Technology Acceptance Model (TAM)

(Venkatesh et al., 2003). According to Davis (1989), user-friendly applications are more likely to be adopted by the general population. Evidence suggests that effort-oriented considerations are more prominent at the onset of a new behavior when process issues pose obstacles, but these considerations are eventually overshadowed by concerns of instrumentality (Davis et al., 1989). This finding is consistent with the work of Davis (1989), Davis et al. (1989), and Venkatesh and Davis (2000) (Diaz & Loraas, 2010). Deng et al. (2011) found that Web-based question and answer services (WBQAS) significantly predict users' willingness to use these services. Predictions regarding performance and effort, along with other enabling and social factors, play a role in determining whether an individual will actually use a product (Helena Chiu et al., 2010).

H2: There is a positive relationship between effort expectancy towards towards bingobox technology adoption consumers behavioral intention in malaysia during epidemic of Covid-19.

Social Influence

How much importance does a person place on others' opinions about their use of technology? This question, discussed in Diaz and Loraas (2010), is similar to the concept of "subjective norm" in the TAM 2 extension. According to Moore and Benbasat (1991), "image" refers to the extent to which a person's social status is enhanced through the use of a technological innovation. People's behavior is influenced by how they believe others perceive them because of their use of technology, whether these perceptions are explicit or implicit.

According to TAM 2, perceived utility and ease of use significantly influence utilization intentions for required systems. However, in voluntary situations, social impact components are not relevant. The use of technology significantly affects subjective norms (Schepers & Wetzels, 2007). Subjective norms impact perceived usefulness through internalization, where people incorporate social influences into their perceptions of usefulness, and identification, where people use a system to gain status and influence within a work group, thereby improving their job performance, especially in the early stages of experience (Ling Keong et al., 2012).

H3: There is a positive relationship between social influence towards bingobox technology adoption consumers behavioral intention in malaysia during epidemic of Covid-19.

Facilitating Conditions

The term "facilitating conditions" refers to the extent to which a person believes that the organizational and technological infrastructure is equipped to support the use of a system. This concept is similar to the model of personal computer use proposed by Thompson et al. (1991). Both technology and organizational environments are considered factors in determining whether a situation is deemed a facilitating condition (Keong et al., 2012). Drawing from the concept of perceived behavioral control, the UTAUT construct aims to describe how an organization seeks to overcome obstacles to system use and how a potential user plans to navigate these obstacles. This measure has the same predictive power as effort expectation in forecasting declines in use after initial acceptance.

H4: There is a positive relationship between facilitating conditions towards bingobox technology adoption consumers behavioral intention in malaysia during epidemic Covid-19.

Hedonic Motivation

In the context of technology, hedonic motivation refers to the delight or pleasure derived from using a certain piece of technology (Brown and Venkatesh, 2005). Hedonic motivation, defined as perceived joy, has been shown to have a direct impact on technology adoption and use in the field of information systems (IS) (e.g., van der Heijden, 2004; Thong et al., 2006). Studies indicate that hedonic drive is also a significant factor in consumer technology uptake and use (e.g., Brown and Venkatesh, 2005; Childers et al., 2001). Hedonic motivation may influence a consumer's behavioral intention to use a technology.

H5: There is a positive relationship between hedonic motivation towards bingobox technology adoption consumers behavioral intention in malaysia during epidemic of Covid-19.

Price Value

UTAUT was established in the context of an organisational usage scenario, where customers typically incur the cost of their use, but workers do not. It's possible that the price and cost structures influence how much technology is used by customers.

H6: There is a positive relationship between price value towards bingobox technology adoption consumers behavioral intention in malaysia during epidemic of Covid-19.

Habit

As a final component of UTAUT, experience and habit are two distinct yet interconnected concepts. Venkatesh et al. (2003) identified three levels of experience over time: immediately after training, one month later, and three months later. Kim et al (2005), associated habit with learning-induced automaticity, defining it as the tendency to perform actions automatically. Although fundamentally similar, habits have been categorized in two distinct ways. Firstly, habit can be viewed in terms of prior behavior (Kim and Malhotra, 2005). Secondly, habit is defined as the extent to which an individual perceives a behavior as intrinsic.

H7: There is a positive relationship between habit towards bingobox technology adoption consumers behavioral intention in Malaysia during epidemic of Covid-19.

Research Framework

The research framework shown in Figure 1 is developed and modified from the research of P. Brewer & Sebby (2021). This theoretical framework is used to examine the determinants of consumers' behavioural intention. The independent variables, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM) , Price Value (PV) and Habit (HB) are discussed in previous few paragraphs, while dependent variable is Behavioral Intention. In short, the proposed framework in this study helps the public and readers to obtain a deeper insight into the factors of BingoBox technology adoption towards consumer behavioral intention in Malaysia during epidemic of Covid-19.

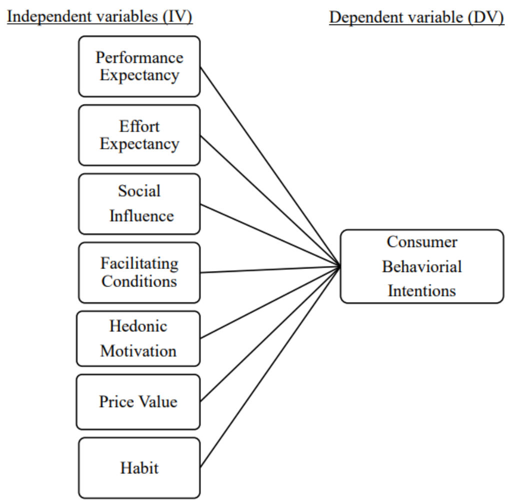

Figure 1 Theoretical Framework of the Research.

Methodology

The research methodology encompasses a method and strategy that involve phases ranging from general assumptions to specific data collection, analysis, and interpretation procedures. This approach is divided into two main parts: data collection strategy and data interpretation strategy. The research will employ a deductive approach, which typically starts with a theory-driven hypothesis that guides data collection and analysis. This method is used to measure and assess the relationship between independent and dependent variables. According to Gulati & Smith (2009), the deductive approach is unique in its reasoning process. It examines existing theories to determine their applicability in specific contexts and is used to test hypotheses. The deductive approach begins with a predicted pattern that is tested against observations, while the inductive approach starts with observations and seeks to identify patterns within them. Thus, the deductive approach is a step-by-step, rational, and structured method focused on deriving conclusions from propositions or premises (Babbie, 2010).

This study utilized a quantitative research approach through an online questionnaire survey with 150 respondents. A pilot test involving 10 respondents was conducted to assess the validity and structure of the questionnaire and to gather feedback. Based on the pilot test results, the questionnaire was adjusted as needed to ensure its relevance and effectiveness. The survey consisted of three sections: Section A focused on general respondent information, Section B addressed independent variables such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HB), which pertain to BingoBox technology adoption and consumer behavioral intentions in Malaysia during the COVID-19 epidemic. Section C concentrated on the dependent variable, which is consumers' behavioral intentions in Malaysia during the epidemic, from the respondents' perspectives. The survey was designed to address and achieve the research questions and objectives, drawing on previous studies by other researchers. Measurement scales validated in existing literature were used, with responses recorded on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The collected data were analyzed using SPSS version 25, employing descriptive statistics, reliability and validity analysis, Pearson correlation, and multiple regression tests to meet the study's objectives.

Table 1 presents the demographic profile of the survey participants. Among the 150 respondents, 41% (n=61) were male, while 59% (n=89) were female. In terms of educational qualifications, 2.7% (n=4) had PMR or PT3 qualifications, and 10% (n=15) held SPM qualifications. Respondents with STPM and Diplomas accounted for 10.7% (n=16) and 30% (n=45) of the sample, respectively. Additionally, 36% (n=54) had a Degree, and 10.7% (n=16) held a Master's degree. Among the respondents, 3.3% (n=5) were retired. The majority of participants were students, comprising 28.7% (n=43), followed by 20% (n=30) working in the public sector, 35.3% (n=53) in the private sector, and 12.7% (n=19) self-employed. The data also reveal that 97.3% (n=146) used BingoBox technology once a month, 0.7% (n=1) ordered food online several times a week, and 2% (n=3) used BingoBox technology once a week during the COVID-19 epidemic.

Table 1
Respondents' Background

Background	Categories	Frequency	Percentage (%)
Gender	Male	61	41
	Female	89	59
Age	20 and below	11	7.3
	21-25	86	57.3
	26-30	38	25.3
	31-35	9	6
	36-40	6	4
Educational level	UPSR	0	0
	PMR/PT3	4	2.7
	SPM	15	10
	STPM	16	10.7
	Diploma	45	30
	Degree	54	36
	Master	16	10.7
	PhD	0	0
Occupation	Student	43	28.7
	Private Sector	53	35.3
	Public Sector	30	20
	Self employed	19	12.7
Frequency usage	Several times a week	1	0.7
	Once a week	3	2
	Once every 2 weeks	0	0
	Once a month	146	97.3

Reliability Analysis and Validity Test

Reliability analysis is assessed using Cronbach's Alpha. Table 2 displays Cronbach's Alpha values for all variables ranging from 0.765 to 0.898, which are significantly higher than 0.70. This demonstrates that the overall alpha coefficient for each subscale is excellent. These high reliability values prove that the whole alpha coefficient value for each variable is acceptable and good condition. As refer to the table above, the Cronbach's Alpha value for Performance Expectancy (α=0.809), Effort Expectancy (α=0.838), Social Influence (α=0.858), Facilitating Conditions (α=0.865), Hendonic Motivation (α=0.765), Price Value (α=0.785), Habit (α=0.830) and Behaviorial Intention (α=0.898). According to Malhotra (2012), reliability in this research is measured using Cronbach Alpha, where a value ≤ 0.60 is considered unreliable, and a value ≥ 0.70 is highly acceptable. Therefore, the results of this survey indicate high reliability. Overall, the reliability analysis of this study is highly satisfactory.

Table 2
Reliability analysis of each variable.

Variable	Number of Items	Cronbach's Alpha
Performance Expectancy	5	0.809
Effort Expectancy	5	0.838
Social Influence	5	0.858
Facilitating Conditions	5	0.865
Hendonic Motivations	5	0.765
Price Value	5	0.785
Habit	5	0.830
Behavioral Intention	5	0.898

Result

In general, the data presented in table 3 indicates noteworthy and favorable correlations between performance expectancy, effort expectancy, social influences, facilitating conditions, hendonic motivation, price value, and habit toward dependent variable which is behavioral intention during epidemic of Covid-19. The results clearly stated that all independent variables : performance expectancy ($r = 0.723$, $p < 0.001$), effort expectancy ($r = 0.653$, $p < 0.001$), social influence ($r = 0.513$, $p < 0.001$), facilitating conditions ($r = 0.519$, $p < 0.001$), Price Value ($r = 0.692$, $p < 0.001$), Hendonic motivations ($r = 0.696$, $p < 0.001$), and habits ($r = 0.749$, $p < 0.001$)

Table 3
Pearson Correlation for Variable Of Study

	PE	EE	SI	FC	PV	HM	HB	BI
PE	1	.825**	.668**	.626**	.623**	.672**	.605**	.723**
EE	.825**	1	.500**	.609**	.675**	.647**	.535**	.653**
SI	.668**	.500**	1	.546**	.702**	.508**	.455**	.513**
FC	.626**	.609**	.546**	1	.529**	.589**	.564**	.519**
PV	.623**	.675**	.702**	.529**	1	.485**	.472**	.692**
HM	.672**	.647**	.508**	.589**	.485**	1	.602**	.696**
HB	.605**	.535**	.455**	.564**	.472**	.602**	1	.749**
BI	.723**	.653**	.513**	.519**	.692**	.696**	.749**	1

**. Correlation is significant at the 0.01 level (2-tailed).

PE= Performance Expectancy, EE =Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions , PV = Price Value, HM = Hendonic Motivations, HB = Habits and BI = Behavioral Intention

The model summary for factors influencing customer behavioral intention is presented in Table 4. The coefficient of determination, R Square, indicates that the four independent variables collectively account for 67.6% (R2 = 0.676) of the total ariance in behavioral intention affected by Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Price Value, Hendonic Motivations, and Habits. The regression model detailed in the table examines how Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Price Value, Hendonic Motivations, and Habits influence customer behavioral intention. The standardized coefficients reveal that Performance Expectancy ($p <$ 0.05, β = 0.348), Effort Expectancy ($p <$ 0.05, β = 0.171), Social Influence ($p <$ 0.05, β = 0.138), Hendonic Motivations ($p <$ 0.05, β = 0.422), Price Value ($p <$ 0.05, β = 0.124), and Habits ($p <$ 0.05, β = 0.322) are all significantly related to customer behavioral intention. However, the variable facilitating conditions ($p >$ 0.05, β = 0.178) is found to be insignificant in relation to behavioral intention.

Table 4
Regression for Customer Intention determine

	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	T	Sig.
(Constant)	.148	.125		1.183	.239
PE	.348	.093	.328	3.754	.000
EE	.171	.085	.187	2.011	.046
SI	.138	.061	.166	2.251	.026
FC	.178	.060	.172	2.973	.256
HM	.422	.067	.487	6.323	.000
PV	.124	.058	.166	2.142	.034
HB	.322	.074	.285	4.330	.000

a.Dependent Variable: Behavioral Intention.
R= 0.822. R square= 0.676. Adjusted R= 0.665. F = 70.173

Discussion

Performance expectancy, defined as the belief that using a technology will enhance performance (Ogunsola & Olojo, 2021), was found to have a significant positive relationship with behavioral intention. These findings align with previous research suggesting that performance expectancy stimulates customer curiosity and purchase intention, particularly when technology offers benefits like quick transactions and efficiency (Wyer et al., 2008; Polacco & Backers, 2018). Additionally, specific aspects such as the speed of transactions and quality of life improvements were highlighted as significant factors influencing behavioral intention towards BingoBox technology during the COVID-19 epidemic (P. Brewer & A.G. Sebby, 2021). Effort expectancy, defined as the ease of using a system (Venkatesh et al., 2003), also showed a significant positive relationship with behavioral intention. This suggests that ease of use is a crucial factor influencing consumer intentions towards mobile payments in BingoBox stores, corroborated by prior studies (Venkatesh et al., 2013; Kim et al., 2010; Tan et al., 2013). Items like transaction efficiency and ease of use had the highest mean scores, emphasizing the importance of these factors (P. Brewer & A.G. Sebby, 2021).

Social influence, defined as the degree to which others' opinions affect an individual's use of new systems (Venkatesh et al., 2003; Alraja, 2015), was found to have a significant positive relationship with behavioral intention. This indicates that social factors, such as recommendations from important people or celebrities, significantly influence consumer behavior towards BingoBox technology (P. Brewer & A.G. Sebby, 2021). Hedonic motivation, defined as the enjoyment derived from using technology (Venkatesh et al., 2003), was found to significantly influence behavioral intention, with a correlation value of 0.686. Enjoyable features of BingoBox technology, such as mobile payments, were significant factors in this relationship (P. Brewer & A.G. Sebby, 2021).

Price value, as a predictor of behavioral intention in the UTAUT2 model (Venkatesh et al., 2012), had a significant positive relationship with behavioral intention. The perception that the benefits of using BingoBox technology outweigh the costs significantly influenced consumer intentions (P. Brewer & A.G. Sebby, 2021). Habit, defined as the automatic tendency to perform certain behaviors (Limayem et al., 2007), also showed a significant positive relationship with behavioral intention. Consumers' habitual use of BingoBox technology, especially compared to traditional methods, significantly influenced their behavioral intentions (P. Brewer & A.G. Sebby, 2021). Therefore, H1, H2, H3, H5, H6 and H7 hypotheses are accepted.

Among all variables, H4 is rejected, indicating that facilitating conditions is the only variable that has no significant relation to behavioural intentions. Facilitating conditions, or the belief in the availability of organizational and technical support (Venkatesh et al., 2003), did not show a significant relationship with behavioral intention. This suggests that despite the availability of supportive infrastructure, it did not significantly influence consumers' intentions during the epidemic, a finding consistent with some previous studies (Chatterjee & Kumar Kar, 2020; Syaifullah et al., 2021).

Conclusions

In conclusion, this study examined the factors influencing the adoption of BingoBox technology and their impact on consumer behavioral intentions in Malaysia during the COVID-19 epidemic, using constructs from Brewer & Sebby’s conceptual model. The findings demonstrated that independent variables such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influences (SI), Hedonic Motivation (HM), Price Value (PV), Habit (HB), and Facilitating Conditions (FC) all significantly correlated with the dependent variable, behavioral intentions. The study utilized methods including descriptive analysis, Pearson correlation analysis, reliability analysis, multiple regression analysis, and hypothesis testing to address the research questions and objectives. The analysis revealed that PE, EE, SI, HM, PV, and HB had a positive and significant relationship with behavioral intention, while FC had a negative yet significant relationship during the epidemic. Notably, the study highlighted the importance of price value, which had a highly significant relationship with behavioral intentions, suggesting that educating consumers about the pricing of these technology stores increases the likelihood of purchase. In summary, BingoBox should continually update its technology features to enhance consumer behavioral intentions during times of crisis.

Significant Implications of the Research

The research successfully examined the dimensions of the conceptual model proposed by (Brewer and Sebby, 2021). The constructs discussed include performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. The concurrent examination of these frameworks contributed to understanding how customers process information and form behavioral intentions, especially in unusual circumstances. Most independent variables demonstrated significant positive relationships with behavioral intentions, with one exception. Consequently, most proposed alternative hypotheses were accepted. The discussions and outcomes of this research, based on the study by Brewer & A.G Sebby (2021), applied the S-O-R model (Stimulus-Organism-Response) to evaluate the behavioral intentions of consumers during the COVID-19 epidemic. This study enhances the literature on BingoBox technology adoption in Malaysia, an emerging area with limited research.

Implication of Managerial Level

The findings from this research offer valuable insights for improving consumer shopping experiences at BingoBox stores. The stores should focus on creating a new integrated customer experience that meets customer expectations, defining the technologies they will invest in, and encouraging the acceptance of these new technologies, as this acceptance is a crucial predictor of behavioral intention. To provide the best technology and meet consumer expectations, BingoBox stores must carefully analyze consumer needs and preferences. The study's findings support the implementation of a strategy based on consumer viewpoints, aiming to provide an integrated shopping experience, increase customer satisfaction, and design an effective shopping model. Additionally, systems should be designed to involve consumers, making the use of these systems a natural behavior as infrastructure issues are resolved. It is essential to develop technical infrastructure to update and track product data regularly, ensure consistency, and match in-store data with data from other channels through integrated inventory systems. BingoBox should raise awareness of their innovations across all channels and work towards creating a positive brand image, as campaigns alone are insufficient. The critical implementation for BingoBox stores is to ensure sustainable customer interactions.

Ethical considerations

This study is voluntarily participation and the respondents agreed to take part in the study. Information gathered during this study is confidential.

Conflict of Interest

The authors declare that they have no conflict of interest.

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