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Urban Air Delivery: What Malaysians think about it?

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Abstract
Drone delivery services are being investigated for their potential adoption in Kuala Lumpur, Malaysia, amid the growing challenges of e-commerce expansion and traffic congestion. The aim is to explore urban residents' willingness to adopt this technology and to identify key factors that influence acceptance. Data were collected from 300 residents and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). Findings reveal that performance expectations, social influence, and convenience significantly impact adoption, while concerns about safety, privacy, and regulation continue to serve as barriers. The study highlights the need for improved infrastructure, clear regulations, and addressing consumer concerns to ensure the successful integration of drone delivery.

Keywords: Drone Delivery; Smart Logistics; Autonomous Delivery Systems; Consumer Behaviour

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1.0 Introduction

The rapid growth of E-commerce has given consumers more choices, increasing their power in the supply chain and shifting operations toward demand-driven models (Perboli et al., 2021). Consequently, suppliers are necessitated to adjust their strategies by establishing flexible and agile supply chains capable of accommodating the evolving expectations of consumers, especially concerning last-mile delivery. Last-mile delivery pertains to the concluding segment of the supply chain, wherein products are conveyed from a warehouse or distribution center to the end consumer (Archetti & Bertazzi, 2020). This segment is often the most expensive and inefficient part of the supply chain, accounting for up to 50% of logistics costs (Bosona et al., 2020). These challenges have prompted researchers to explore solutions that improve the efficiency of last-mile delivery, particularly in urban environments (Kiba-Janiak et al., 2021).

In response, logistics companies are turning to innovative solutions, such as drones, to meet customer demand. Companies such as FedEx, DHL, and Amazon are exploring the integration of Unmanned Aerial Vehicles (UAVs) into their delivery operations (Li et al., 2023). Drones have previously been used in fields such as military operations (Ko et al., 2021) and rural medical deliveries (Sham et al., 2022). Previous researchers have noted a lack of discussion regarding the use of drones for parcel delivery within the broader context of supply chain and logistics. While drone technology has yet to see widespread adoption for last-mile delivery, pilot programs by companies like Amazon and Google highlight its strong potential for future use (Eskandaripour & Boldsaikhan, 2023). However, the topic of urban users' acceptance of drone delivery remains unexplored mainly, presenting a significant gap that this study aims to address.

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In light of the prevailing global phenomenon of urbanization, it is projected that by the year 2050, 68% of the global population will reside within urban environments (Gu et al., 2021), traffic congestion is likely to continue worsening, making drones a potential solution. This initiative will mitigate the conventional approaches to last-mile logistics, which are predominantly dependent on vehicles fueled by fossil resources and exacerbate ecological challenges such as the emission of greenhouse gases and the phenomenon of global warming (Hwang et al., 2020). Drones have been seen as more energy-efficient and could help reduce the environmental impact of delivery operations, a growing concern, particularly in countries like Malaysia (Sham et al., 2022).

Despite the clear benefits, consumer acceptance of drone delivery remains uncertain. Research on drone delivery has explored various operational models, including truck-drone hybrids and scheduling optimisation (Madani & Ndiaye, 2022). Nevertheless, there exists a pressing necessity to concentrate on comprehending consumer perspectives, particularly within the urban milieu of Malaysia, wherein E-commerce assumes a critical function in the economic landscape. The Unified Theory of Acceptance and Use of Technology (UTAUT) framework, along with its augmented iteration, UTAUT2, offers a comprehensive structure for elucidating the determinants that affect consumer acceptance of innovative technologies (Penney et al., 2021). This framework was further utilised to explore user acceptance in Malaysian urban areas. Factors such as hedonic motivation, price value, and perceived risk are crucial in determining consumer acceptance. Therefore, the primary purpose of this study is to investigate the acceptance of delivery services within the urban population of Kuala Lumpur. Specifically, the research objective is to determine the factors that affect the acceptance of drone delivery among the urban population in Malaysia.

2.0 Literature Review

The utilization of drone technology has attracted considerable scholarly interest in the past few years., transitioning from the early stages of research to practical applications in various fields, including medical deliveries and agricultural inspections (Ayamga, 2021). As its utilization proliferates across various nations, scholars have concentrated on comprehending the determinants that affect societal endorsement of this nascent technology, especially within the framework of delivery services.

A preeminent paradigm for the examination of technology acceptance is the Technology Acceptance Model (TAM), which was initially proposed by Davis et al (1989). TAM posits that two key factors, which include perceived ease of use and perceived usefulness, influence users' intentions to adopt new technology. Perceived usefulness pertains to the extent to which an individual perceives that technology will augment their professional efficacy, whereas perceived ease of use pertains to the anticipated effort that the individual expects to invest while engaging with the technology (Wang et al., 2023). This theoretical framework has been extensively utilized to analyze consumer motivations concerning the acceptance of drone-based delivery services.

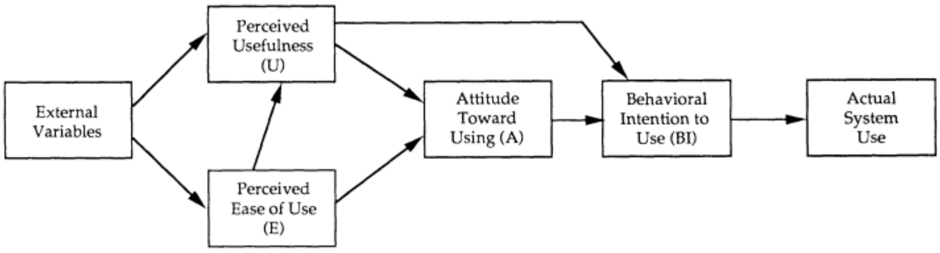

Fig. 1: Technology Acceptance Model (TAM)
Source: Davis et al., 1989

In conjunction with the Technology Acceptance Model (TAM), the Diffusion of Innovation (DOI) theoretical framework, conceptualized by Rogers in 1962, has been employed to assess the assimilation of technological advancements (Kim et al., 2025). The DOI framework posits that five determinants significantly influence the acceptance of technology: relative advantage, compatibility, complexity, trialability, and observability. These determinants evaluate the comparative benefits of a novel technology against prevailing solutions, its alignment with consumer needs and values, the ease of utilization, the extent to which consumers can experiment with the technology, and the visibility of the technology's advantages to external observers. Kim et al. (2025) utilized this theoretical construct to explore the technological variables that shape perceptions regarding drone delivery, underscoring the pivotal influence of rapid delivery and reliability on the acceptance of drone delivery systems by users. Their research elucidated that these characteristics play a vital role in alleviating perceived risks and addressing privacy issues, which are prevalent impediments to technology adoption.

Choe et al. (2021) proposed an alternative framework, blending TAM with the Theory of Planned Behavior (TPB). The Theory of Planned Behavior posits that an individual's actions are significantly influenced by their intention to engage in such actions, which is in turn molded by their attitudes, subjective norms, and perceived behavioral control. Within the framework of drone adoption, the research integrated perceived risks (concerning privacy and safety), functional advantages, and relational characteristics (pertaining to the interaction between the consumer and the technology provider.

Additionally, Liu et al. (2020) utilized the UTAUT2 framework, which integrates constructs including performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and habitual behavior. Their investigation also incorporated perceived risk as a salient variable influencing consumer acceptance of delivery drones. Conducted with 379 valid respondents, the research found that facilitating conditions, effort expectancy, and perceived risks significantly influenced the intention to adopt drones, which, in turn, influenced actual usage.

On the other hand, Kapser and Abdelrahman (2020) applied the UTAUT2 model to the adoption of autonomous vehicles for last-mile delivery in Germany. Their study focused on behavioural intention as the key predictor of adoption, showing that all the variables tested (including facilitating conditions, effort expectancy, and perceived risks) had a significant impact on the intention to use autonomous vehicles. They collected data from 501 respondents, and the analysis confirmed that these factors played a crucial role in shaping users' adoption behaviour.

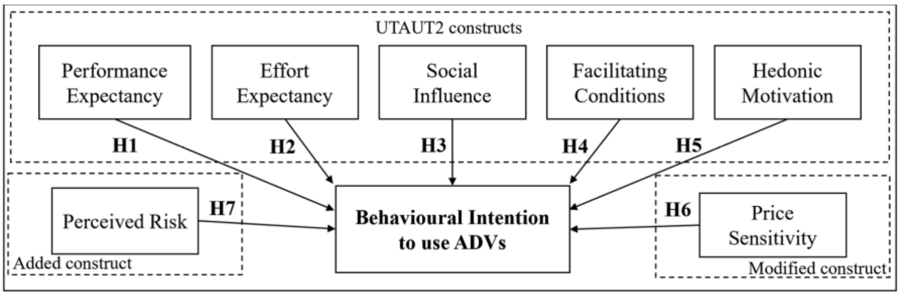

Fig. 2: Framework for acceptance of autonomous vehicles in last-mile delivery.
Source: Kapser and Abdelrahman (2020)

2.1 Proposed hypothesis and theoretical framework

This study will employ the UTAUT 2 framework, concentrating on four principal dimensions: performance expectancy (PE), effort expectancy (EE), social influence (SI), and price sensitivity (PS). Additionally, it will incorporate perceived risk (PR) as a factor influencing behavioural intention (BI) to adopt drone delivery technology based on its significance in previous studies. The independent variables aim to assess users' behavioural intention, which is a reliable indicator of actual adoption behaviour.

Performance expectancy refers to how valid the potential user expects technology to be in their daily life. Performance expectancy has long been stated as one of the significant variables in measuring users' adoption of technology (Kapser & Abdelrahman, 2020). It is considered the most robust and reliable variable in predicting behavioural intention. Autonomous last-mile delivery methods (i.e., drones) are believed to be more customer-friendly, providing greater flexibility and improved delivery times compared to the alternative methods (Ostermeier et al., 2023).

H1: Performance expectancy positively influences behavioural intention to adopt drone delivery services.

On the other hand, the effort expectancy is defined as the potential user's perception of the difficulty of using this technology. If technology is too complicated to use or understand, it will hinder its adoption. Effort expectancy has also been shown to be a significant variable in measuring behavioural intention (Kasper & Abdelrahman, 2020). In this context, the complexity of perception might stem from the technical "know-how" required to use the technology. It might require the use of smartphones to interact with the drone and order it at the right time and place. Some potential users might view this as too cumbersome, thus preventing them from adopting this service (Kasper & Abdelrahman, 2020).

H2: Effort expectancy positively influences behavioural intention to adopt drone delivery services.

Apart from that, the construct of social influence measures how family, friends, and the surrounding social environment perceive a person's use of a particular technology. This is also proven to be an essential predictor of technology adoption (Kasper & Abdelrahman, 2020). Potential users may be influenced by peer pressure to adopt a particular technology or exhibit a specific behaviour

H3: Social influence positively influences behavioural intention to adopt drone delivery services.

As we cannot escape the fact that consumers bear the cost of using technology, the price construct has also been incorporated into the research framework based on the UTAUT model. This is defined as the customer's trade-off between the monetary cost and the benefits of using the delivery drone. When the perceived benefits provided by using drone delivery exceed the monetary cost, it will have a positive impact on behavioural intention (López-Fernández, 2020).

H4: Price sensitivity positively influences behavioural intention to adopt drone delivery services.

Although many other factors can influence adoption, the perceived risks have consistently been the primary factor affecting consumers' adoption of new technology. When new technology is offered to consumers, a lack of understanding and prior experience creates a sense of uncertainty, making potential buyers wary of the risks it might hold. For example, in studies on the adoption of automated vehicles, perceived risk has consistently been identified as a significant factor affecting consumer adoption (Kenesei et al., 2022).

H5: Perceived risk positively influences behavioural intention to adopt drone delivery services.

All the factors mentioned were used to assess consumers' behavioural intention to use drone deliveries in this context of the study. Behavioural intention reflects the motivation to perform a task and is closely linked to actual technology adoption. A positive behavioural intention increases the likelihood of adoption, while a harmful intention reduces the chances of adopting the technology.

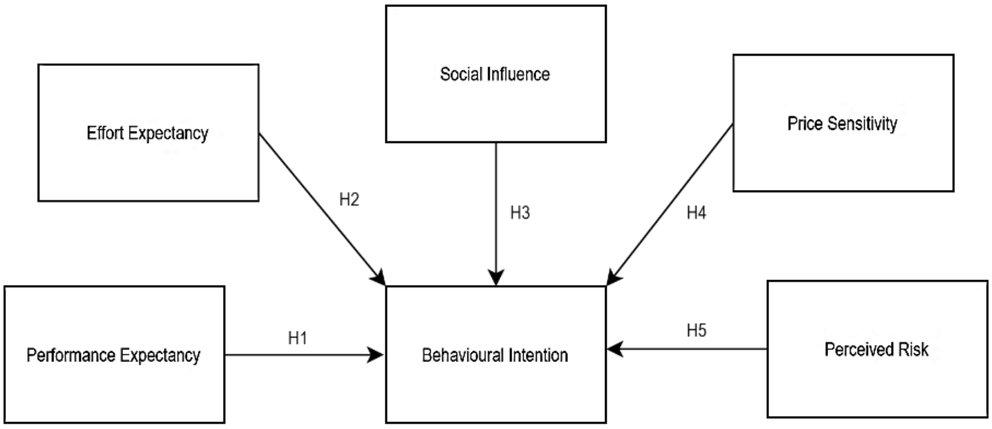

Figure 3: Theoretical framework
Source: Author's own work.

3.0 Methodology

Data collection was conducted through an online questionnaire, using a similar method to that employed by Mathew et al. (2023), which was distributed to the urban population in Kuala Lumpur. The online platform facilitated the efficient collection of a large sample for analysis (Mathew et al., 2023); therefore, the study adopted a similar method. The questionnaire included items adapted from previous studies that used the UTAUT2 model (Kasper & Abdelrahman, 2020). The survey was systematically organized into two distinct sections, wherein Section A encompassed five demographic inquiries and Section B included 30 statements (five corresponding to each variable) designed to elucidate the determinants that affect the proclivity to utilize drone delivery services (Mathew et al., 2023). Participants evaluated their responses employing a 5-point Likert scale, which was similarly utilized by Mathew et al. (2023), who had previously executed a comparable investigation on drone acceptance utilizing a Likert scale that spanned from 1 (strongly disagree) to 5 (strongly agree).

3.1 Sampling

The demographic cohort of this investigation is comprised of the existing inhabitants of Kuala Lumpur, which, as reported by the Department of Statistics Malaysia, was estimated to be approximately 1.79 million (≈ 1.8 million); hence, utilizing the Krejie and Morgan table formula, a total sample size of 384 (Krejie & Morgan, 1974) is recommended for the research endeavor.

3.2 Data Analysis

This study used a variance-based method, PLS-SEM, to analyse the data (Mathew et al., 2023). This method estimates the relationships between variables and has been widely used in similar studies employing the UTAUT2 model (Mathew et al., 2023). PLS-SEM was chosen because it is suitable for both small and large sample sizes, making it an appropriate choice for this study. The analysis began by assessing the Reliability and validity of the constructs, following similar methods to those conducted by Mathew et al. (2023).

3.2.1 Reliability

The Reliability of the constructs used in this study was measured using Cronbach's Alpha, a commonly employed method to assess internal consistency (Bergmann et al., 2022). It assigns a reliability score ranging from 0 to 1. Internal consistency reflects how closely related the items are within the same construct, while Reliability ensures the consistency of the test results. A Cronbach's Alpha value of 0.7 or higher indicates good Reliability. Constructs with values below 0.7 are considered unreliable and may be excluded from further analysis. In this study, all constructs have reported a value of 0.8 or above, as shown in Table 2, indicating a good reliability score.

3.2.2 Validity

Validity pertains to the extent to which a construct is measured with precision. This process guarantees that the instruments employed genuinely represent the conceptual frameworks intended (Bergmann et al., 2022). Within the scope of this research, both convergent and discriminant validity will undergo evaluation. Convergent validity will be assessed through the Average Variance Extracted (AVE), with values exceeding 0.5 signifying acceptable validity. Discriminant validity will be examined via the Heterotrait-Monotrait (HTMT) ratio, as advocated by Dirgiatmo (2023). HTMT values falling below 0.9 substantiate the discriminant validity of the constructs.

3.2.3 Hypothesis testing

Hypothesis testing was performed utilizing the bootstrapping technique within the SmartPLS 3 software environment. This methodology produces t-statistics employed to ascertain the significance of the associations among the variables under investigation. A t-value exceeding 1.96, as derived from the standard normal distribution, signifies a statistically meaningful relationship, thereby leading to the rejection of the null hypothesis. Conversely, if the t-value falls below 1.96, the relationship lacks significance, resulting in the rejection of the hypothesis (Gupta & Arora, 2020).

4.0 Findings

Data analysis was carried out after collecting the required responses—the first step involved evaluating the Reliability and validity of the measurement items.

Table 2: Cronbach's alpha value for variables.

Variable	Cronbach's Alpha
Behavioural intention	**0.803**
Effort expectancy	**0.852**
Performance expectancy	**0.852**
Perceived risk	**0.909**
Price sensitivity	**0.871**
Social influence	**0.763**

All variables listed in Table 2 had Cronbach's Alpha values exceeding 0.7, confirming that the Reliability of the constructs is acceptable based on the Bergmann et al. (2022) study.

Table 3: AVE values for all variables.

Variable	AVE
Behavioural intention	**0.508**
Effort expectancy	**0.629**
Performance expectancy	**0.628**
Perceived risk	**0.730**
Price sensitivity	**0.645**
Social influence	**0.509**

Similarly, all variables demonstrated AVE values greater than 0.5, establishing their convergent validity. Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, which was chosen over the Fornell-Larcker and cross-loading criteria due to its superior accuracy in measuring discriminant validity (Dirgiatmo, 2023). The HTMT values obtained from the analysis are shown in Table 4.

Table 4: Heterotrait-monotrait ratio (HTMT)

	Behavioural intention	Effort expectancy	Performance expectancy	Perceived risk	Price sensitivity	Social influence
Behavioural intention						
Effort expectancy	**0.717**					
Performance expectancy	**0.709**	0.851				
Perceived risk	**0.462**	**0.200**	**0.253**			
Price sensitivity	**0.309**	**0.303**	**0.501**	**0.429**		
Social influence	**0.777**	**0.696**	0.897	**0.468**	**0.712**	

All values in Table 4 are below the threshold of 0.9. While some values are close to 0.9, none exceed it, thereby confirming the discriminant validity of the constructs.

Using the bootstrapping procedure in SmartPLS 3, t-statistics were generated to test each hypothesis proposed in the previous chapter. Table 4 and Figure 4 present the path coefficients and the structural model derived from the bootstrapping process.

Figure 4 illustrates the path model that represents the relationships between several independent variables and the dependent variable, behavioural intention. The model includes path coefficients, which quantify the strength and direction of these relationships. Among the variables, performance expectancy has a path coefficient of 0.164, indicating a positive but relatively weak relationship with behavioural intention. This suggests that a one-standard-deviation increase in performance expectancy results in a 0.164 increase in the likelihood of behavioural intention. Effort expectancy shows a stronger positive relationship with behavioural intention, with a coefficient of 0.283. This implies that a one-standard-deviation increase in effort expectancy leads to a 0.283 increase in the likelihood of engaging in the behaviour, reflecting the greater importance of ease or effortlessness in forming intentions.

The social influence variable has the highest coefficient at 0.370, indicating that it plays a significant role in shaping behavioural intention. A one-standard-deviation increase in social influence results in a 0.370 increase in behavioural intention, highlighting the power of social factors in influencing decisions. Conversely, price sensitivity shows a negative relationship with behavioural intention, as indicated by its coefficient of -0.166. This suggests that as price sensitivity increases, the behavioural intention decreases, reflecting how concerns about price may discourage certain behaviours. Lastly, perceived risk has a positive relationship with behavioural intention, with a coefficient of 0.237. This means that as perceived risk increases, so does behavioural intention, possibly due to individuals becoming more cautious or aware of potential outcomes. Each variable contributes differently to the formation of behavioural intention, with varying degrees of influence, both positive and negative.

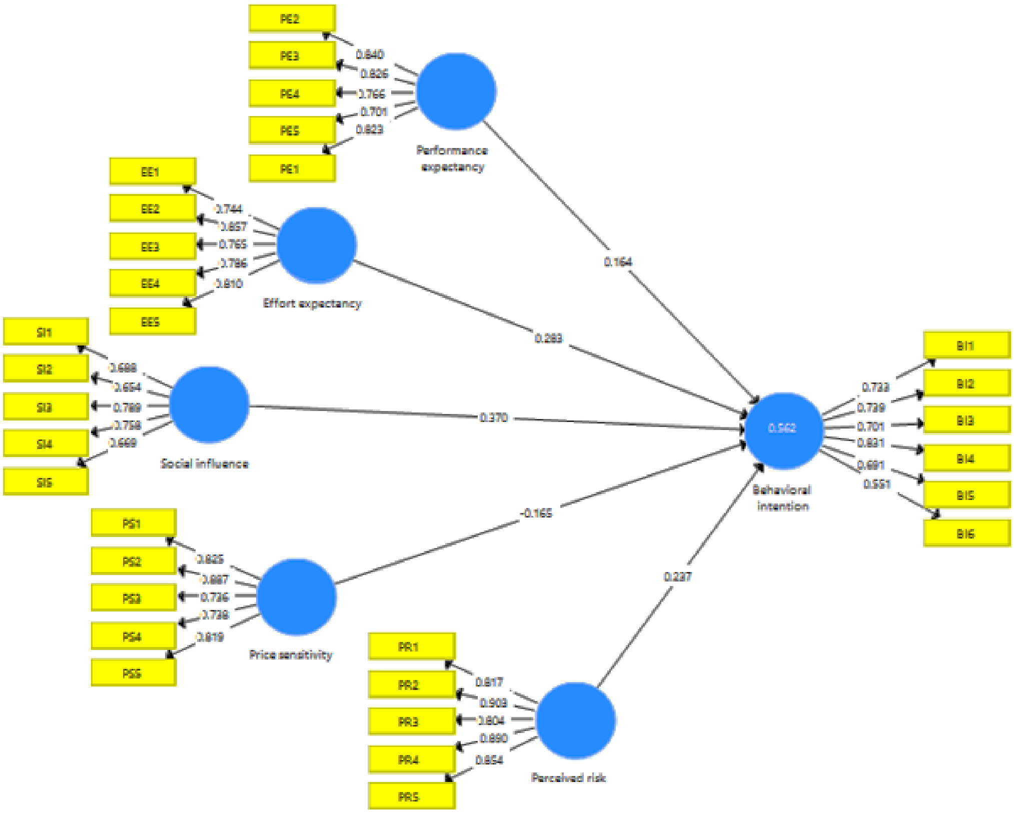

Figure 4: Path model

Behavioural intention recorded an R^2 value of 0.562, indicating that approximately 56% of the variance in behavioural intention is explained by the independent variables. Figure 5 illustrates the strength of these relationships, ranked from highest to lowest

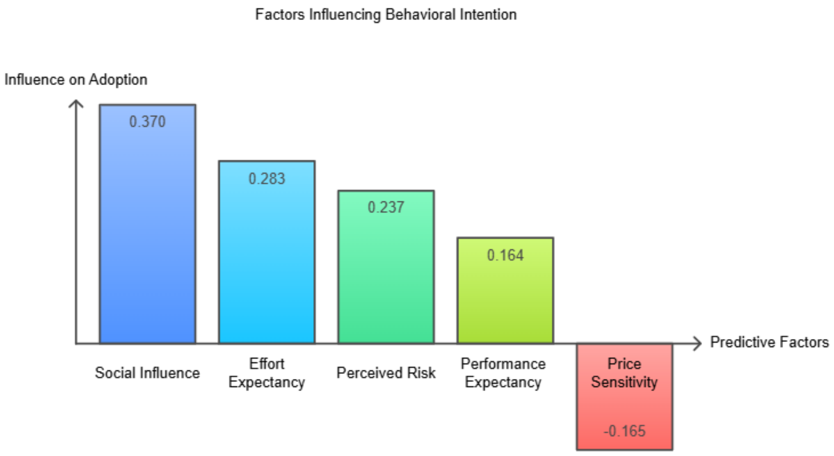

Figure 5: Strength of relationship from highest to lowest

Table 5: Coefficient Analysis

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics (|O/STDEV|)	P Values
Effort expectancy -> Behavioural intention	0.283	0.291	0.104	2.711	0.003
Performance expectancy -> Behavioural intention	0.164	0.147	0.113	1.455	0.073
Perceived risk -> Behavioural intention	0.237	0.230	0.091	2.593	0.005
Price sensitivity -> Behavioural intention	-0.165	-0.138	0.101	1.637	0.051
Social influence -> Behavioural intention	0.370	0.379	0.106	3.507	0.000

The obtained values are sufficient to either accept or reject the hypotheses. Only the remaining five hypotheses were tested in this phase. The results of the analysis provide statistical support for the following hypotheses:

H2: Effort expectancy positively influences behavioural intention to adopt drone delivery services.
H3: Social influence positively influences behavioural intention to adopt drone delivery services.
H5: Perceived risk positively influences behavioural intention to adopt drone delivery services.
On the other hand, the following hypotheses were not supported by the analysis:
H1: Performance expectancy positively influences behavioural intention to adopt drone delivery services.
H4: Price sensitivity positively influences behavioural intention to adopt drone delivery services.

5.0 Discussion

This research utilizes the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory to elucidate the behavioral intention behind the adoption of drone delivery services. In alignment with the TAM framework, effort expectancy (ease of use) and social influence emerge as significant predictors of adoption intention, thereby underscoring the critical roles of user-friendliness and peer influence during the initial phases of technology adoption (Penney et al., 2021). In contrast to conventional TAM outcomes, performance expectancy did not exhibit significance, indicating that users may not yet possess a comprehensive understanding of the advantages offered by drone delivery. Moreover, the affirmative correlation between perceived risk and adoption intention further implies that awareness of risk may coexist with a degree of cautious optimism, an area that merits further investigation (Li & Li, 2023). These results suggest that, in the context of nascent technologies, prioritizing ease of use, social endorsement, and transparent communication regarding risks may be vital for facilitating adoption, even in circumstances where performance benefits remain ambiguous.

The DOI theory enhances these findings by highlighting five essential characteristics of innovations relative advantage, compatibility, complexity, trialability, and observability that influence adoption (Hanson & Olsson, 2020). The outcomes of this study are consistent with the DOI's emphasis on complexity (effort expectancy) and observability (social influence) as pivotal factors driving adoption. As noted by Kim et al. (2025), the speed and reliability of delivery, which are fundamental indicators of relative advantage, play significant roles in alleviating perceived risks and privacy concerns, which are prevalent obstacles to adoption. By synthesizing TAM and DOI, this investigation offers a substantial contribution to the comprehension of drone delivery adoption, positing that simplifying usage, enhancing social visibility, and effectively communicating the benefits of innovation are imperative strategies to promote adoption at this emerging juncture.

6.0 Conclusion & Recommendations

This study acknowledges several limitations that may have influenced the results. Notably, the limited availability and exposure of drone delivery services in Kuala Lumpur likely affected respondents' perceptions, potentially explaining why performance expectancy and price sensitivity were not significant forecasters of adoption aim. Additionally, the relatively small sample size, constrained by a limited geographical area, may have affected the generalizability and precision of the findings, which reflect the situation in Malaysia as a whole. Increasing the sample size in upcoming research would improve the strength of generalisation in the analysis.

Based on these limitations, future research is recommended to broaden the scope by including more diverse populations, such as residents in rural areas where drone delivery could have higher practical relevance due to limited traditional delivery infrastructure. Moreover, examining the perspectives of service providers and their readiness to integrate drone delivery into logistics and supply chain operations could provide valuable insights. Practically, businesses aiming to introduce drone delivery services should tailor their marketing and adoption strategies to align with the key factors identified in this study — social influence, effort expectancy, and perceived risk to better cater to consumer preferences and increase acceptance.

Acknowledgement

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Paper Contribution to Related Field of Study

This paper contributes to the fields of technology adoption and logistics innovation by empirically exploring consumer intentions to adopt drone delivery services in Kuala Lumpur, integrating the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory for a comprehensive analysis. It challenges traditional assumptions by showing that performance expectancy and price sensitivity may have limited influence in early adoption stages, while social influence and effort expectancy play more critical roles. These findings offer fresh theoretical insights into the adoption of emerging technologies and provide practical guidance for businesses and policymakers seeking to promote drone delivery services, thereby advancing both academic understanding and industry applications in innovative delivery systems.

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