Critical factors characterizing consumers' intentions to use drones for last-mile delivery: Does delivery risk matter?

Christian Nedu Osakwe[a,b,c,*], Marek Hudik[d], David Říha[e], Michael Stros[f], T. Ramayah[g,h,i,j,k]

[a]Rabat Business School, International University of Rabat, Morocco
[b]Department of Economics and Finance, South Ural State University, Chelyabinsk, Russia
[c]University of Pretoria's Gordon Institute of Business Science, Johannesburg, South Africa
[d]Faculty of Business Administration, Prague University of Economics and Business, W. Churchill Sq. 4, Prague 3, Czech Republic
[e]Faculty of Business Administration, Prague University of Economics and Business Prague, W. Churchill Sq. 4, Prague 3, Czech Republic
[f]University of Applied Sciences and Arts of Southern Switzerland (SUPSI), Fernfachhochschule Schweiz, Ueberlandstrasse 12, 3900, Brig, Switzerland
[g]School of Management, Universiti Sains, Malaysia
[h]Internet Innovation Research Center, Newhuadu Business School, Minjiang University, China
[i]Department of Management, Sunway University Business School (SUBS), Malaysia
[j]Faculty of Economics and Business, Universiti Malaysia, Sarawak, Malaysia
[k]Faculty of Accounting and Management, Universiti Tunku Abdul Rahman (UTAR), Malaysia

*Corresponding author. Rabat Business School, International University of Rabat, Morocco. Email: chris.osakwe12@outlook.com

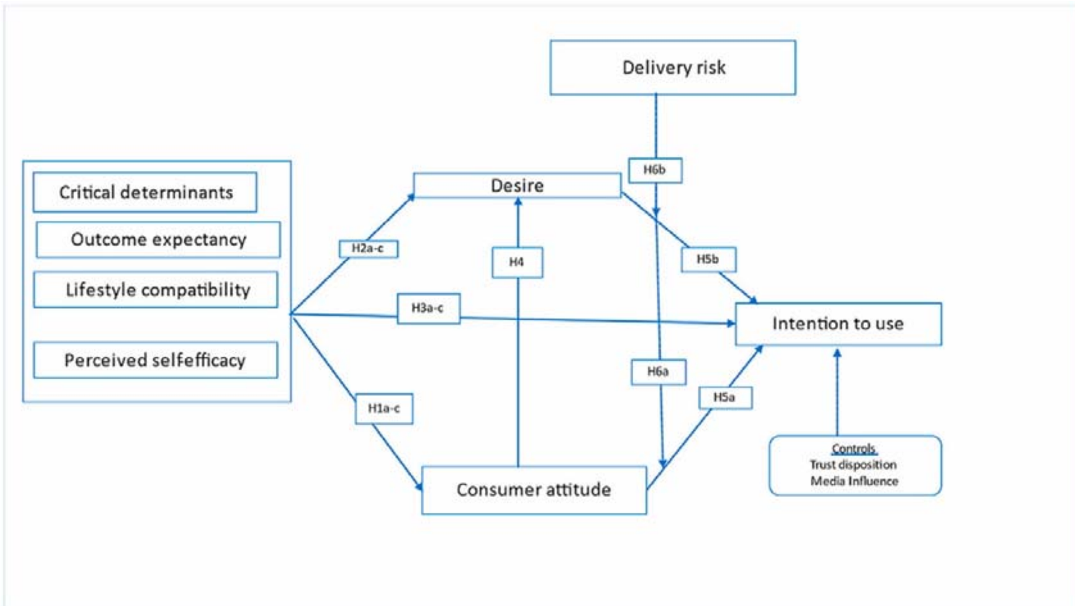
Highlights

- The present study identifies important independent factors underpinning the motivations to use drones for last-mile delivery.
- The moderating role of delivery risk is further investigated.
- Study is underpinned by the social cognitive theory and the model of goal-directed behavior.
- The findings emanating from this study hold important implications for research on commercial drones and managerial practice.

Abstract

Uncrewed Aerial Vehicle (UAV), commonly known as a drone, has become popular in military and recreational circles. Although their usage in commerce is relatively low, a continuous rise in commercial use, especially for last-mile delivery, in the future is anticipated. Consequently, there is a necessity for a greater understanding of consumers' readiness to accept the latest technological application to increase knowledge, business, and managerial practice. Specifically, this study aims to investigate consumers' intentions to deploy drones for last-mile delivery. The study applies the social cognitive theory and the model of goal-directed behaviour. It investigates the effect of outcome expectancy, lifestyle compatibility, perceived self-efficacy, consumer attitude, and the desire of usage for delivery drones among European millennial consumers. Additionally, it examines whether delivery risk moderates the influence of attitude and desire to use delivery drones. The authors discovered that the aforementioned are positively related to consumer attitude. Consumer attitude as such is positively associated with the desire and intention to use this method of delivery. Furthermore, the intention to use drone delivery is positively influenced by the desire for this delivery, outcome expectancy, and lifestyle compatibility. These findings indicate the importance of desire and lifestyle compatibility as predictors. At the theoretical level, the results support the perspective that social cognitive theory, together with the model of goal-directed behaviour, is an adequate framework to account for consumer intentions.

Graphical abstract



Keywords: Drones; Social cognitive theory; Goal-directed behaviour; Last-mile delivery; Consumer intentions; Czech Republic;

"Gartner predicts that in 2026, more than one million drones will be carrying out retail deliveries, up from 20,000 today." (Goasduff, 2020).

1. Introduction

Drones have existed since the early twentieth century. Until recently, they have largely been confined to military warfare (Cook, 2007, as cited in Baloch and Gzara, 2020). The use of drones beyond military applications, government surveillance (Leclercq-Vandelannoitte and Aroles, 2020), and mundane activities such as photography, now attracts significant commercial interest, especially among retailers and logistics firms (Baloch and Gzara, 2020; Joerss et al., 2016; Roca-Riu and Menendez, 2019; Ramadan et al., 2017). However, their usage in commerce is still low. Current expectations predict a continuous rise of delivery drones in the future (Bain & Company, 2018). Similarly, according to Gartner, by 2026, more than a million drones will be used for retail deliveries, up from the current estimate of 20,000 (Goasduff, 2020).

Although usage creates problems with airspace management between uncrewed and crewed aircraft (Galkin, 2021), successful commercial drone delivery potentially modifies last-mile delivery and, ultimately, customer fulfilment. Possibly, commercial drones will work in tandem with user-friendly mobile applications, thus allowing consumers to easily monitor and trace their ordered merchandise (Aurambout et al., 2019). Subsequently, reducing delivery risks.

Although scholars demonstrate a keen interest in the study of drone delivery services (Aurambout et al., 2019; Hwang and Kim, 2021; Perera et al., 2018; Raj and Sah, 2019; Yoo et al., 2018; Zhu, 2019), there exists limited empirical exploration of consumer readiness to embrace this delivery type. This is unsurprising as drone delivery is still an emerging trend and piloted in phases. Interestingly, a recent survey (Urban, 2018) found that approximately 26% of respondents expect to use drone delivery services in the next few years. This finding further reinforces the necessity for an enhanced understanding of consumer readiness to accept this technology and to inform professionals.

As consumer behavioural intention is a useful indicator of actual adoption behaviour and willingness to pay additional service charges, studies of the potential contributory factors to usage intentions, in terms of drone delivery, play a key role to provide valuable guidance for research practitioners, drone developers, retailers, and logistics companies. Among others, the study by Hwang et al. (2019b) identified perceived innovativeness and attitudes as factors that would influence consumers' intentions to adopt a drone food delivery service. Furthermore, Hwang et al. (2019a) highlight positive and negative anticipated emotions as predictors of the desire to use drone delivery and, ultimately, usage intentions. Similarly, while Khan et al. (2019) emphasized consumer privacy as a key concern for acceptance, research by Yoo et al. (2018) further highlight the relative advantages of speed, complexity, innovativeness, performance, and reduced privacy risks as determinants of consumer attitudes towards drone delivery and, in turn, adoption. Additional studies assert that attitude, perceived behavioural control, and personal and subjective norms play an important role in initial acceptance (Kim and Hwang, 2020). In addition, the image of a delivery service is a strong determinant of both the desire and intention to use (Hwang and Choe, 2019; Hwang and Kim, 2021).

The above studies contribute to the authors initial understanding of this emerging trend. Nonetheless, these studies are confined to the Asian consumer context and imply the need to incorporate diverse consumer contexts into a study of consumer acceptance. The study extends the research to the analysis of consumer intentions and their determinants in the European market. Moreover, none of the above studies, has investigated whether delivery risk - considered a concern for potential users (Sah et al., 2020; Yoo et al., 2018; Zhu et al., 2020) - might play an important moderating role especially in the influence of consumer factors such as attitude and desire.

Data for this study is collected in the Czech Republic. The country presents ideal conditions to test assumptions on consumer acceptance of this emerging technology artifact. Czech consumers are highly sophisticated and digitally literate and drone usage is popular (Tsiamis et al., 2019). Czechs are thus more likely to be early adopters of drone delivery. This rising relevance of drones is also indicated by the increased importance of drone start-ups (Tracxn, 2021).

It needs to be noted that each country has specific regulations of drone utilization. These regulations may differ across the EU (DroneRules, 2021). The Czech regulation of UAVs is the responsibility of the Civil Aviation Authority (CAA). These regulations for commercial drones include the obligation to register, to have an aerial work permit, and a liability insurance up to 880,000 euro. The drone must be operated by a licensed pilot. Furthermore, reporting accidents/incidents is mandatory for commercial drones (DroneRules, 2021). These regulations increase costs in relation to other possible alternatives.

Since it is commonly understood that a multitude of factors may affect the adoption of innovations, this alone is an incentive for academic exploration of the phenomenon. Moreover, since commercial drone usage is in its infancy and is piloted by the companies identified above, more research grounded in established theory is needed to understand this emergent trend. The reader may also review the call to action by Aydin (2019) and Tsai and Tiwasing (2021); 6). Besides other works on technology adoption, this study integrates the social cognition theoretical perspective (c.f. Bandura, 1992) with the model of goal-directed behaviour (Perugini & Bagozzi, 2001, 2004) in the exploration of critical determinants of drone usage among potential EU consumers.

Based on the two theoretical perspectives, this advance research in commercial drone acceptance and especially, in regard to last mile delivery, through focusing on six potentially critical factors: (1) outcome expectancy; (2) lifestyle compatibility; (3) perceived self-efficacy; (4) delivery risk; (5) consumer attitude, and (6) consumers' desire relative to intention to deploy these services. In addition, this study examines whether the first three identified factors play a role in the formation of both positive consumer attitudes towards and desire to use the technology. The notion that delivery risk moderates the influence of both attitude and desire on intentions is further explored, especially among millennials who are often described in the literature to be early adopters of emergent innovations.

The most important contribution to the extant body of knowledge to this new field is the identification and empirical analysis of the critical determinants behind drone acceptance, which has been formed by these theories. Based on an extensive literature review, the authors conclude that this research represents a dual theoretical perspective of the social cognitive theory and the goal-directed behaviour model in the exploration of consumer drone motivations. The study and its empirical revelations extend the research into drone acceptance, particularly in terms of the potential to be used effectively for customer delivery. Thereby, increases its commercial success. The study also complements previous efforts (Hwang et al., 2019a, 2019b, 2019c; Khan et al., 2019; Yoo et al., 2018), and together with these, the findings provide a foundation to augment understanding of the topic. At the general level, this work contributes to the literature through analysis of the demand for delivery (e.g., Kim et al., 2017) and advances the understanding of the critical factors associated with consumer acceptance.

2. Theoretical background and hypotheses

2.1. Social cognitive theory (SCT)

SCT is a widely accepted model of individual behaviour (Liu, 2016; Ratten and Ratten, 2007; Schunk, 2012; Sun et al., 2020). It is a descendant of the social learning theory (Bandura, 1977a) and builds upon the foundations of individual and group psychological behaviour. It proposes the existence of continuous reciprocal causation among environmental factors, cognitive factors, and human behaviour (Bandura, 1986, 2006).

SCT argues that behaviour is affected by outcome expectations and self-efficacy. The latter refers to personal belief of one's capability to perform a particular behaviour (Bandura, 1977b; Hsu et al., 2004). It conceptually overlaps with the notion of perceived behavioural control in the research stream of planned behaviour (Ajzen, 1991; Chen and Hung, 2016; Yang, 2012). The concept of self-efficacy is prominent as it recognizes that expectations of positive outcomes from certain behaviour is meaningless if one doubts their capability to successfully execute such behaviour in the first place (Compeau et al., 1999). In other words, the desire to engage in a particular form of behaviour is not in itself enough; one must also have the perceived ability to accomplish (Hsu et al., 2004).

SCT considers human behaviour to be dynamic that is, individuals device plans based on their anticipation of future outcomes, and revise their plans, if necessary (Bandura, 2005). Due to its adaptive nature, SCT is often used to examine the reasons for individuals who adopt certain behaviours (Compeau and Higgins, 1995; Straub, 2009). Accordingly, it has been applied to account for the adoption of technologies, such as computers (Conrad and Munro, 2008) or AI (Suseno et al., 2020). SCT implies that decisions as to whether and the extent to use technology are related to self-efficacy, positive outcome expectations (Hsu et al., 2004; Liu, 2016) and personal characteristics, such as, lifestyle compatibility (Bandura, 1986; Rogers, 1995). Therefore, this study, includes these factors as antecedents of consumer intentions.

2.2. The model of goal-directed behaviour (MGB)

MGB enriches motivational theories and in relation to emerging technologies adoption by highlighting the role of desire (Bagozzi, 2007). Desire is defined as a state of mind whereby an agent has personal motivation to perform an action or achieve a goal (Perugini and Bagozzi, 2004). In fact, according to scholars, “the motivational content in decision-making is constituted by the desire to perform a certain behaviour, and desire energizes intentions” (Perugini and Bagozzi, 2004; 11). Importantly, desire, which is an intrinsic motivational state, is conceptually different from attitude and intention. Attitude represents how favourable or unfavourable a person perceives the behaviour to be (Ajzen, 1991). This means that attitude reflects favourable or unfavourable evaluations of a specific behaviour (Tsai and Tiwasing, 2021; Yang, 2012; Yoo et al., 2018). Intention is defined as “the degree to which a person has formulated conscious plans to perform or not perform some specified future behaviour” (Warshaw and Davis, 1985; 214). It reflects “how much of an effort they are planning to exert” (Ajzen, 1991; 181). A key distinction between intention and desire is that intention ‘is relatively now-oriented, but desire usually does not have time limitation’ (Yi et al., 2020). According to the MGB, desire is a proximate cause of intentions, while attitudes are a distal cause. The influence of attitudes on intentions is mediated by desire (Leone et al., 1999).

MGB has been applied to highlight the role of desires to explain the variability of intentions and behaviours (Bagozzi, 2007; Perugini and Bagozzi, 2001). For example, previous research indicates that desire is an important predictor of intentions to work with social robots (Piçarra and Giger, 2018) and to use drone food delivery services (Hwang and Kim, 2021). Desire has also been found as an important factor to form bicycle travellers’ loyalty (Han et al., 2017a). In line with MGB, desires, next to attitudes and intentions, comprise the model.

2.3. Critical determinants

Applying SCT, the following three components are used as independent variables of the construct of critical determinants: a) outcome expectancy, b) perceived self-efficacy, and c) lifestyle compatibility.

Bandura (1977b) defines outcome expectancy as the expected ability to execute a course of action successfully and achieve the expected outcome (Ratten and Ratten, 2007). Sheeshka et al. (1993) state that expected outcomes are dependent upon expectations of performance in given situations and is also interpreted by other scholars to reflect performance expectancy of the object (Venkatesh et al., 2003). Consequently, the contribution of outcome expectancy alone to the prediction of behaviour may be limited. Therefore, in line with SCT, perceived self-efficacy is included as an additional independent variable.

Self-efficacy is defined as the belief that one has the capability to perform a behaviour (Bandura, 1986). Perceptions of self-efficacy have shown to influence decisions about the behaviour to engage (Compeau and Higgins, 1995; Liu, 2016; Ratten and Ratten, 2007; Yang, 2012), and also affect emotional responses (Bandura, 1977b).

Rogers (1995) notes that an individual might accept an innovation if it is compatible with their lifestyle. More importantly, according to Armstrong et al. (2014), consumers in a society do not just buy products but also the values and lifestyles that such products represent. Another aspect is that groups share and maintain coherence and compatibilities in their lifestyles (Veal, 1993). Earl (1983) suggests that lifestyle is the search for coherence and compatibility in various aspects of life (Boateng et al., 2016). Additionally, recent reports suggest that in addition to the pertinent issue of the regulatory framework surrounding drone delivery operations (Baur and Hader, 2020), there exists several psychological factors that include attitude, delivery risk, desire, self-efficacy, and outcome expectancy (Hwang et al., 2019b; Kim et al., 2021; Yoo et al., 2018; Zhu et al., 2020). The latter constitute the successful uptake of drone delivery by end-market users. These authors examine the above issues in relation to the initial acceptance of drone delivery through the development of a research model based on SCT and MGB and the European potential customers in the market as an empirical case.

2.4. Effect of critical determinant components on consumer attitude

Outcome expectancy is hypothesized to explain attitudes and attitude formation (Huang et al., 2015). Empirical studies indicate that in various contexts a positive association between outcome expectancy and self-efficacy on the one hand, and attitudes on the other (Baker-Eveleth and Stone, 2008; Stone and Baker-Eveleth, 2013). Attitudes are also affected by the lifestyle compatibility (Hanafizadeh et al., 2014; Tsai and Tiwasing, 2021) as emphasized by Rogers (1995). Consequently:

H1a. Outcome expectancy has a positive influence on consumer attitude.

H1b. Perceived self-efficacy has a positive influence on consumer attitude.

H1c. Lifestyle compatibility has a positive influence on consumer attitude.

2.5. Effect of critical determinant components on desire

According to MGB, desire is distinct from attitudes and intentions (Perugini and Bagozzi, 2001). Earlier research suggests that a stronger desire to act is associated with a greater self-efficacy and greater outcome expectancy (Sekerka and Bagozzi, 2007). More so, according to Yi et al. (2020) there is a significant positive relationship between perceived behavioural control, conceptually similar to self-efficacy, and desire in the Airbnb context. Further, since lifestyle compatibility has been previously found to positively influence attitudes towards technology (Hanafizadeh et al., 2014; Tsai and Tiwasing, 2021), it is also expected also that the notion of lifestyle compatibility will have an independent and significant direct effect on consumers' desire to use drone for their last-mile delivery. Especially, if customers feel that the drone usage is congruent with their interests and how their purchased items are to be delivered. Therefore:

H2a. Outcome expectancy has a positive influence on desire.

H2b. Perceived self-efficacy has a positive influence on desire.

H2c. Lifestyle compatibility has a positive influence on desire.

2.6. Effect of critical determinant components on intention to use

SCT predicts that outcome expectations and self-efficacy influence individuals' actual ability to exhibit a particular behaviour. This effect is substantiated by several studies in both clinical and organizational settings, in relation to a wide variety of behaviour (Abood and Conway, 1988; Compeau and Higgins, 1995; Maddux et al., 1986; Nel and Heyns, 2017; Yoo et al., 2018). In their study, Nel and Heyns (2017) discuss that perceived self-efficacy positively and significantly influences usage intentions. Moreover, Abood and Conway (1988), as well as Maddux et al. (1986), found that self-efficacy and outcome expectancy made approximately equal contributions to the prediction of behavioural intentions. Extant research also indicates that lifestyle compatibility is positively associated with intention (Hanafizadeh et al., 2014; Koenig-Lewis et al., 2010; Wessels and Drennan, 2010). As a result:

H3a. Outcome expectancy has a positive influence on intention to use.

H3b. Perceived self-efficacy has a positive influence on intention to use.

H3c. Lifestyle compatibility has a positive influence on intention to use.

2.7. Effect of consumer attitude on desire

According to MGB, attitude is an important predictor of desire, which suggests that when consumers have a positive attitude, they have a higher level of desire (Bagozzi, 2007; Perugini and Bagozzi, 2001; Leone et al., 2004). Empirical studies confirm the effect of attitude on desire (Hwang et al., 2019b; Piçarra and Giger, 2018). Therefore:

H4. Consumer attitude has a positive influence on desire.

2.8. Effect of consumer attitude and desire on intention to use

As stated by Hwang et al. (2019b), the relationship between attitude and behavioural intentions is confirmed by many existing theories. According to Ajzen (1991), attitude is a crucial factor that explains individuals' behavioural intentions and plays an important role in their prediction. This is also supported by empirical studies and among which are Brand et al. (2020), Chen and Hung (2016), Han et al. (2017b), Hwang et al. (2020) and Tsai and Tiwasing (2021). Therefore:

H5a. Consumer attitude has a positive influence on intent to use.

According to Perugini and Bagozzi (2001), the desire to engage in certain behaviour is the most important factor that affects intention/behaviour. Furthermore, the relationship between desire and behavioural intentions is empirically confirmed in consumer-behaviour-related research (Hwang et al., 2019a). Consequently, it is concluded that desires are important predictors of intentions (Hwang and Kim, 2021; Perugini and Bagozzi, 2004; Piçarra and Giger, 2018). Desire is created based on positive or negative evaluations as a critical role in behavioural intentions formation (Bagozzi, 2007; Han and Yoon, 2015; Hwang and Choe, 2019; Yi et al., 2020). Therefore:

H5b. Desire has a positive influence on intention to use.

2.9. The moderating influence of delivery risk

Low-flying drones have raised public concern. According to Ren and Chen (2020), more than 80% of the flight activities of light and small uncrewed drones take place below 120 m. Their increased use raises awareness of their risk (Luppicini and So, 2016). Following which, researchers from numerous countries and disciplines studied the risks posed by civilian drones (e.g., Mingyuan, 2019). Users have higher expectations for new technologies, but also exhibit negative attitudes when usage results in unexpected adverse consequences. One explanation for this phenomenon is that customers may have little information about products or services that use innovative technologies. They may, therefore, perceive greater risk due to uncertainty or lack of trust (Herzenstein et al., 2007; Lee, 2009). Perceived risk is defined as "the nature and amount of risk perceived by a consumer in contemplating a particular purchase decision" (Cox and Rich, 1964; 33). This may also be described as the risk of a loss in a choice situation (Taylor, 1974). Klauser and Pedrozo (2017) define the perceived risk in the use of drone delivery services as the subjectively determined expectation of a loss. According to Bauer (1960), perceived risk theory explains how consumers understand risk to avoid negative outcomes in their purchase decisions. Consumers seek to avoid or reduce negative outcomes rather than increase benefits through risk-taking (Im et al., 2008).

These findings lead to the conclusion that delivery risk, following the research of Sah et al. (2020:6) is explained as "the probability of drone malfunctioning and not being able to deliver the product [on time]" could moderate the relationship between potential users' attitude and their intentions to use (H6a). This supports the findings of several authors (e.g., Sun, 2014) that consumers are reluctant to use new technology-based services because of possible risks. On the other hand, it has been revealed that venturous, innovative consumers take a risk to try new services or products (Nakamura, and Kajikawa, 2018; Wright et al., 2014). Therefore, it is assumed that a positive relationship between consumer attitude and intent to use is reduced in the presence of a perceived delivery risk (i.e., H6a). This proposition is supported by the fact that increased positive attitudes towards drone delivery that, in turn, decrease risk concerns about safety, privacy, and security (Parker et al., 2012, 2016). However, Zhu (2019) reveals that consumers with positive attitudes towards drone delivery focus on issues with security and privacy than the benefits specific to this delivery method. According to Lopez-Nicolas and Molina-Castillo (2008), customers are also concerned about delivery failure of their packages due to theft, damage, or other unexpected events. Furthermore, customers who expect drones to fail may develop an unfavourable attitude and therefore are less likely to use it (Robinson, 2017; Vijayasarathy, 2004). Similarly, consumers who feel unsafe about food delivery services have fewer positive perceptions of these services (Chen, 2013; Hwang and Choe, 2019; Martins et al., 2014). Consequently, customers' attitudes directly influence their behaviour in regard to their actual system usage (Davis, 1989; Lee, 2009). This attitude arises from the individual assessment of said behaviour, and their behavioural intention. This is explained as the "strength of one's willingness to exert effort while performing certain behaviours," Lee (2009). Considering the preceding discussion:

H6a. Delivery risk negatively moderate the positive influence of consumer attitude on usage intentions.

Further studies by Nakamura and Kajikawa (2018), Hwang and Cloe (2019) and Yi et al. (2020) imply that possible risks mitigate the influence of consumers' desire of a product. Another study conducted by Soffronoff et al. (2016) also proposes that providers are viewed less favourable when using drone delivery services due to possible risks. In fact, according to Sah and colleagues, delivery risk is a vital mitigating factor of potential users' acceptance of drone and especially in the logistics context. Therefore, the following is proposed:

H6b. Delivery risk negatively moderate the positive influence of desire on intention to use.

The above hypotheses are summarized in the form of a research model in Fig. 1.

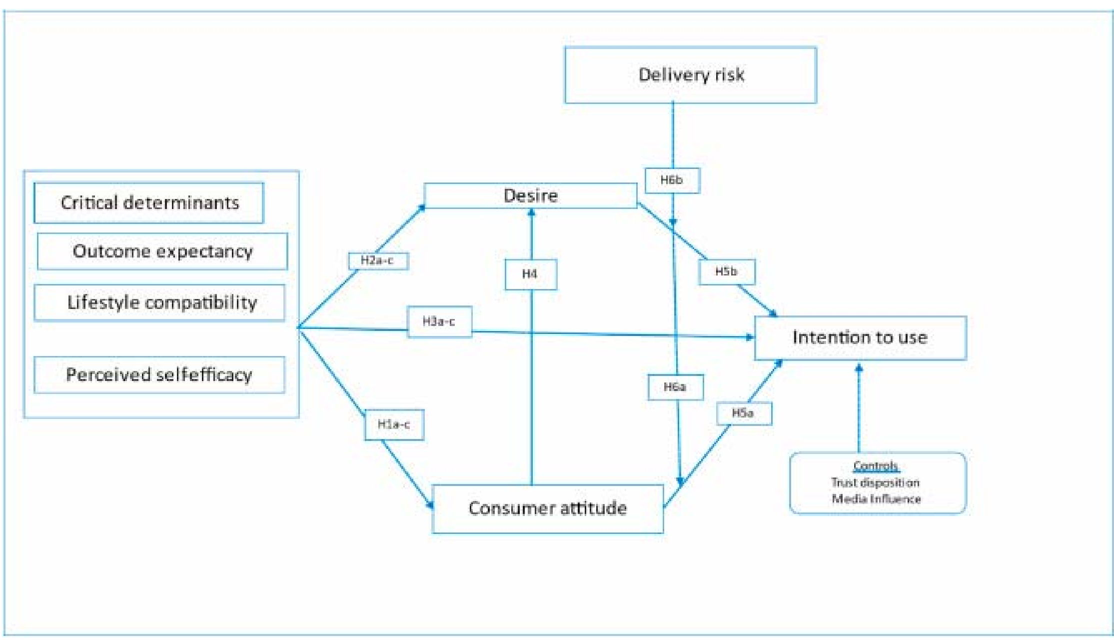


Fig. 1. Proposed research model.

Table 1. Measures.

Attitude	ATTDE1 I think that using drone delivery is a good idea
	ATTDE2 I think that using drone delivery to receive a package would be a wise idea
	ATTDE3 I have positive feelings towards using a drone as part of my shopping activities
Lifestyle Compatibility	COMPAT1 Using drone delivery would fit my lifestyle COMPAT2 Using drone to receive orders would fit well with how I like to do my shopping COMPAT3 Using drone to receive products would be compatible with how I would like to receive my products
Delivery Risk	DERISK1 The package the drone is carrying might be stolen DERISK2 The package the drone is carrying might be damaged by others DERISK3 Product delivery may take too long or be incomplete
Desire	DESIRE1 I desire to use drone delivery services when ordering items and/or products from a shop DESIRE2 My desire to use drone delivery services when ordering items is strong DESIRE3 I want to use drone when ordering goods/items.
Intention to Use Drone	INTENT1 Using drone delivery to receive products is something I would do INTENT2 I would use drone delivery to receive my order INTENT3 I could see myself using drone delivery to receive a package INTENT4 Given the resources I predict I would use drone delivery
Media Influence	MMEDIA1 I have often seen articles about drone delivery in the media MMEDIA2 I got a lot of information from media about drone delivery MMEDIA3 I understood more about drone delivery through the media
Outcome Expectancy	OEXPECT1 My expectation about drone delivery is that it will provide many unique features (item dropped) OEXPECT2 I expect that drone delivery will offer me superior value for money OEXPECT3 Using drone delivery will offer me greater convenience than any other methods OEXPECT4 I expect good service quality when using drone for my shopping delivery OEXPECT5 My expectation in general is that drone delivery will offer me important benefits
Perceived Self-Efficacy	SEFICACY1 I feel that I am capable of using drone technology for shopping purposes SEFICACY2 I believe I have the necessary skills and/or knowledge to use drone for product delivery SEFICACY3 I feel confident understanding how to operate drone for receiving orders SEFICACY4 Generally speaking I could handle a more challenging technological innovation than drone delivery
Trust Disposition	TRUSTDIS1 I generally trust other people TRUSTDIS2 I generally have faith in humanity TRUSTDIS3 I generally trust other people unless they give me reason not to TRUSTDIS4 I feel that people are generally reliable

3. Methodology

3.1. Measurement instruments

All measurement instruments are adapted and modified from previous research, thus ensuring content validity. In particular, the measures of perceived self-efficacy and outcome expectancy were derived from Ratten and Ratten (2007), while lifestyle compatibility is adapted from Boateng et al. (2016). The measure of desire originates from Hwang et al. (2019b), consumer attitude from Yoo et al. (2018). To measure the intention to use, we relied on the research of Hwang et al. (2019b) and Yoo et al. (2018). The measurement items for delivery risk and media influence (control variable 1) were drawn from Yoo et al. (2018), while the measurement items for trust disposition (control variable 2) were obtained from the research of Gefen (2000) and Kim et al. (2008). The measurement scale is anchored on a five-point Likert scale and ranges from strongly disagree (1) to strongly agree (5). Table 1 provides an overview of the measures and their corresponding items.

3.2. Research sample and data collection procedure

This study targeted a younger population aged between 17 and 35 years. This population segment is known to be early adopters and heavy users of digital technologies (Alexander and Kent, 2020; Leon, 2018; Osakwe et al., 2021; Thusi and Maduku, 2020). An online survey was utilized for the data collection and through the chain-referral sampling approach (Kuo et al., 2020). The survey took place in the Czech Republic from February to April 2019.549 completed responses were received. 48.8% of the respondents were females, while males constituted 51.2% of the sample. A further breakdown of the sample characteristics is displayed in Table 2.

Table 2. Sample characteristics (n = 549).

Category	Sub-category	Frequency
Gender	Female	268
	Male	281
Age	17–24	521
	25–30	25
	Missing response	3
Nationality	Asian	10
	Czech	455
	European, non-Czech	75
	Other	9
Respondent familiarity with drone	I have seen a drone physically	398
	I have seen a drone on the internet	113
	I have seen a drone on the TV	34
	Missing response	4
Respondent use of drone	No	413
	Yes	136

3.3. Data analysis and software

The study utilized component-based structural equation modeling, also known as PLS-SEM, mainly due to the exploratory nature of the study (Hair et al., 2019a; Osakwe et al., 2021). Moreover, the statistical objective is geared toward in-sample and out-of-sample prediction; thus, reinforcing the appropriateness of PLS-SEM (Hair et al., 2019b, 2020; Ofori et al., 2021). Additionally, PLS-SEM is a well-established method in the literature and renders the research results more comparable to previous literature (Chen and Hung, 2016; Liu, 2016; Tsai and Tiwasing, 2021). SmartPLS 3.3.3 software (Ringle et al., 2015) is used for the statistical analysis.

Following the suggestions of Anderson and Gerbing (1988), we adopted a two-step approach for the evaluation of the hypothesized model. In the first step, in line with the guidelines of Hair et al. (2020) and Ramayah et al. (2018), testing comprised the validity and reliability of the instruments used. The second step, the researchers ran the structural model to test the developed hypotheses.

Since data was collected using a single source, the issue of Common Method Bias is examined based on the recommended approach by Kock (2015) and Kock and Lynn (2012). In this method, all variables are regressed against a common variable. If the VIF ≤3.3, then there is no bias from the single-source data. Table 3 displays, the analysis yielded VIF of less than 3.3; thus, single/source bias is not a serious data issue.

Table 3. Full collinearity testing.

Construct	VIF
Attitude	3.007
Lifestyle Compatibility	2.923
Delivery Risk	1.040
Desire	2.630
Intention to Use Drone	2.918
Media Influence	1.155
Outcome Expectancy	2.029
Perceived Self-Efficacy	1.525
Trust Disposition	1.115

4. Results

4.1. Measurement model assessment

For the measurement model, assessment includes the loadings, average variance extracted (AVE), and the composite reliability (CR). The values of loadings should be ≥ 0.708, the AVE, ≥ 0.5, and the CR, ≥ 0.7. As shown in Table 4, the AVEs are all higher than 0.5 and the CRs, higher than 0.7. The loadings are also acceptable, with only one loading less than 0.708 (Hair et al., 2020).

Table 4. Convergent validity, construct and indicator reliabilities.

Construct	Item	Loadings	CR	AVE
Attitude	ATTDE1	0.897	0.909	0.768
	ATTDE2	0.867		
	ATTDE3	0.865		
Lifestyle Compatibility	COMPAT1	0.865	0.906	0.763
	COMPAT2	0.871		
	COMPAT3	0.885		
Delivery Risk	DERISK1	0.766	0.853	0.659
	DERISK2	0.864		
	DERISK3	0.803		
Desire	DESIRE1	0.910	0.919	0.791
	DESIRE2	0.846		
	DESIRE3	0.910		
Intention to Use Drone	INTENT1	0.892	0.932	0.774
	INTENT2	0.909		
	INTENT3	0.873		
	INTENT4	0.843		
Media Influence	MMEDIA1	0.857	0.901	0.751
	MMEDIA2	0.868		
	MMEDIA3	0.876		
Outcome Expectancy	OEXPECT1	0.695	0.859	0.549
	OEXPECT2	0.708		
	OEXPECT3	0.731		
	OEXPECT4	0.763		
	OEXPECT5	0.804		
Self-Efficacy	SEFICACY1	0.837	0.886	0.661
	SEFICACY2	0.830		
	SEFICACY3	0.797		
	SEFICACY4	0.788		
Trust Disposition	TRUSTDIS1	0.763	0.857	0.601
	TRUSTDIS2	0.721		
	TRUSTDIS3	0.855		

In addition to the above, the team assessed the discriminant validity using the heterotrait–monotrait (HTMT) criterion proposed by Henseler et al. (2015) and updated by Franke and Sarstedt (2019). The HTMT values should be ≤ 0.85 according to the stricter criterion and ≤0.90 according to the more lenient criterion to consider the discrimination validity between two latent variables as established. Table 5 illustrates the values of HTMT are all lower than 0.9. This confirms that the research constructs are sufficiently distinct from each other. Also, the bootstrapped confidence interval upper limit did not indicate values of 1. This signifies that for any random sample selected from the original distribution, the lower and upper bounds of the 95% bias corrected and accelerated (BCa) confidence interval of the HTMT values should not include one (1) (Hair et al., 2019a). Accordingly, the validity test confirms that the corresponding nine constructs used in this study are conceptually distinct and can be used, therefore, in the analysis of the hypothesized relations (Franke and Sarstedt, 2019).

4.2. Structural model assessment

Supported by Hair et al. (2020), reports of the path coefficients, the standard errors, t-values, and p-values for the structural model used a 5000-sample re-sample bootstrapping procedure (also see Ramayah et al., 2018). Table 6 summarizes the criteria used to test the developed hypotheses. Based on prior research, two control variables, Media Influence and Trust Disposition are added, but neither variable is significant.

Table 5. Discriminant validity based on the HTMT criterion.

Construct	1	2	3	4	5	6	7	8	9
1. Attitude									
2. Lifestyle Compatibility	0.798								
3. Delivery Risk	0.131	0.111							
4. Desire	0.797	0.830	0.129						
5. Intention to Use Drone	0.808	0.857	0.080	0.773					
6. Media Influence	0.270	0.306	0.058	0.367	0.231				
7. Outcome Expectancy	0.809	0.661	0.104	0.657	0.670	0.289			
8. Perceived Self-Efficacy	0.575	0.548	0.056	0.483	0.481	0.300	0.569		
9. Trust Disposition	0.077	0.115	0.160	0.125	0.101	0.214	0.250	0.288	

Table 6. Results of the hypotheses testing

Hypothesis	Relationship	Std Beta	Std Error	t-value	p-value	BCI LL	BCI UL	f^2
H1a	**Outcome Expectancy → Attitude**	**0.381**	**0.039**	**9.834**	**$p < 0.001$**	**0.317**	**0.445**	**0.231**
H1b	**Lifestyle Compatibility → Attitude**	**0.408**	**0.040**	**10.144**	**$p < 0.001$**	**0.346**	**0.478**	**0.266**
H1c	**Self-Efficacy → Attitude**	**0.131**	**0.038**	**3.459**	**$p < 0.001$**	**0.067**	**0.192**	**0.030**
H2a	**Outcome Expectancy → Desire**	**0.089**	**0.041**	**2.177**	**0.015**	**0.023**	**0.156**	**0.010**
H2b	**Lifestyle Compatibility → Desire**	**0.440**	**0.045**	**9.846**	**$p < 0.001$**	**0.366**	**0.512**	**0.240**
H2c	Self-Efficacy → Desire	0.011	0.038	0.282	0.389	−0.052	0.072	0.000
H3a	**Outcome Expectancy → Intention**	**0.078**	**0.038**	**2.075**	**0.019**	**0.023**	**0.149**	**0.009**
H3b	**Lifestyle Compatibility → Intention**	**0.403**	**0.043**	**9.470**	**$p < 0.001$**	**0.340**	**0.477**	**0.195**
H3c	Self-Efficacy → Intention	−0.001	0.033	0.045	0.482	−0.055	0.051	0.000
H4	**Attitude → Desire**	**0.325**	**0.045**	**7.234**	**$p < 0.001$**	**0.250**	**0.398**	**0.104**
H5a	**Attitude → Intention**	**0.259**	**0.048**	**5.404**	**$p < 0.001$**	**0.177**	**0.333**	**0.071**
H5b	**Desire → Intention**	**0.191**	**0.045**	**4.268**	**$p < 0.001$**	**0.115**	**0.263**	**0.043**
H6a	Attitude*Delivery Risk → Intention	−0.055	0.054	1.021	0.154	−0.111	0.085	0.005
H6b	Desire*Delivery Risk → Intention	0.003	0.047	0.057	0.477	−0.048	0.116	0.000
Control1	Media Influence → Intention	−0.036	0.028	1.270	0.102	−0.085	0.008	0.003
Control2	Trust Disposition → Intention	0.012	0.037	0.324	0.373	−0.096	0.054	0.000

First, analysis of H1a, H1b and H1c predicts consumer attitude. The R^2 for attitude is 0.598 ($Q^2 = 0.454$) demonstrating that 59.8% of the variance in attitude is explained by the three variables taken together. Outcome expectancy ($\beta = 0.381$, $p < 0.01$), Compatibility ($\beta = 0.408$, $p < 0.01$) and self-efficacy ($\beta = 0.131$, $p < 0.01$) are positively related to attitude and supports H1a, H1b, and H1c.

Next, the predictors of desire are reviewed. The R^2 for desire was 0.591 ($Q^2 = 0.462$), which reveals that 59.1% of the variance in desire is explained by modeled variables namely, outcome expectancy, compatibility, self-efficacy, and attitude. Outcome expectancy ($\beta = 0.089$, $p < 0.05$), and compatibility ($\beta = 0.440$, $p < 0.01$) are positively related to desire but self-efficacy ($\beta = 0.011$, $p > 0.05$) is not a significant predictor. This supports H2a and H2b, but not H2c. Attitude ($\beta = 0.325$, $p < 0.01$) is positively related to desire and consequently supports H4.

Finally, the predictors of intention are tested. The R^2 for intention to use is 0.661 ($Q^2 = 0.506$), which specifies that 66.1% of the variance of intention to use is explained by the modeled variables including the moderating effects. Outcome expectancy ($\beta = 0.078$, $p < 0.05$), compatibility ($\beta = 0.403$, $p < 0.01$), attitude ($\beta = 0.259$, $p < 0.01$), and desire ($\beta = 0.191$, $p < 0.01$) are positively related to Intention, while self-efficacy ($\beta = -0.001$, $p > 0.05$) is not a significant predictor of intention. Thus, H3a, H3b, H5a and H5b are supported, but H3c was not.

Equally, delivery risk is appraised as a moderator of the relationship between Attitude and Intention as well as between Desire and Intention to use. Neither the effect of the interaction between attitude and delivery risk ($\beta = -0.055$, $p > 0.05$), nor between the desire and delivery risk ($\beta = 0.003$, $p > 0.05$) are significant. Therefore, H6a and H6b are not supported.

As a result, the following finalized research model in Fig. 2 is derived.

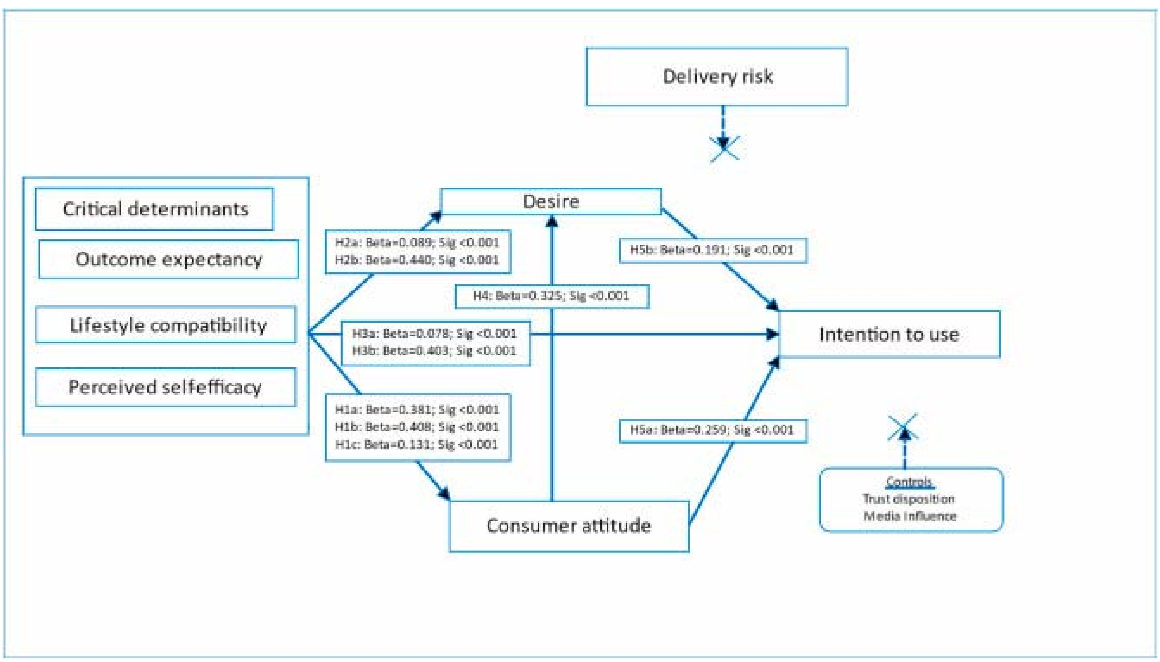


Fig. 2. Finalized research model.

Table 7. Out-of-sample prediction based on PLS predict.

MV	PLS		LM		PLS-LM		
	RMSE	MAE	RMSE	MAE	RMSE	MAE	Q^2_predict
INTENT1	0.691	0.519	0.698	0.521	−0.007	−0.002	0.482
INTENT2	0.697	0.534	0.732	0.55	−0.035	−0.016	0.492
INTENT3	0.724	0.57	0.721	0.554	0.003	0.016	0.452
INTENT4	0.723	0.551	0.768	0.584	−0.045	−0.033	0.401

As this study also aims to assess the out-of-sample prediction of the research model and especially the target construct of intention to use drones, the study employed the PLS-Predict method. With PLS-Predict, researchers can compare their proposed PLS model with a naïve linear model benchmark especially using error metrics such as root mean squared error (RMSE). For further details, relative to PLS-Predict, consult Hair et al. (2020). Shmueli et al. (2019) proposed a holdout sample-based procedure. It generates case-level predictions on an item or a construct level using the PLS-Predict with a ten-fold procedure to verify predictive relevance. They suggest that if all item differences (PLS-LM) are negative, then the model holds strong predictive power. If all differences are positive, then the predictive relevance of the model is not confirmed. If the majority of the differences is negative, there is a moderate predictive power. Finally, if the minority of differences is negative, the model has low predictive power. Based on Table 7, three errors of the PLS model out of four are lower than the LM model, and the Q^2_Predict for the latent variable is 0.591. Thus, one may conclude that the model has moderate predictive power. In particular, the PLS model may to some extent be relied upon to predict potential users' intentions toward drone delivery.

Further investigation to determine if there are potential issues with endogeneity, especially with respect to the direction of causality' the authors employed a range of robust statistical tools namely, Sympson's paradox ratio (SPR), r-squared contribution ratio (RSCR), statistical suppression ratio (SSR), and the nonlinear bivariate causality direction ratio (NLBCDR) (Kock, 2020; Shibin et al., 2020). The robust results in Table 8 indicate that endogeneity is not a problem as the results are above the acceptable limits and further reinforce the utility of the proposed model.

Table 8. Test for endogeneity using different indices.

Index	Research reported value	Acceptable level
Sympson's paradox ratio (SPR)	SPR = 0.813	acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)	RSCR = 0.983	acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)	SSR = 1.000	acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)	NLBCDR = 1.000	acceptable if >= 0.7

5. Discussion and conclusion

5.1. Summary

All three critical variables: outcome expectancy, lifestyle compatibility, and self-efficacy, influence positively consumer attitude. In addition, outcome expectancy and the lifestyle compatibility positively affect both desire and the intention to use. The results also indicate that consumer attitude positively affects desire and the intention to use. The desire itself positively affects the intention to use. Interestingly, the intention to use is not affected by the control variables of media influence and trust disposition. However, surprisingly research results indicate that delivery risk does not in any meaningful way diminish the impact of attitude and desire on intentions.

5.2. Theoretical implications

The results provide several theoretical implications. First, the relevance of SCT for the analysis of intention to use drones in last-mile delivery. In particular, in line with SCT, the study confirms the essential role of outcome expectancy and perceived self-efficacy. However, the effect of perceived self-efficacy is identified on the consumer attitude but not directly on the intention to use. Although contrary in the light of earlier studies that highlight the effect of perceived self-efficacy on the intention to use (Liu, 2016; Nel and Heyns, 2017; Teo, 2009). There are, however, studies that also find no effect of self-efficacy on use intentions (Heerink, 2011; Venkatesh et al., 2003). Furthermore, the result is comparable with studies that conclude the direct effect of self-efficacy on attitudes (Baker-Eveleth and Stone, 2008; Hsu et al., 2004; Stone and Baker-Eveleth, 2013). The research, meanwhile, is further indicative that attitude is an important mechanism to influence the outcome expectancy on use intentions, especially in the context of drone acceptance. Indeed, emerging evidence from the supplementary analysis reveals that attitude mediates the influence of outcome expectancy, and perceived self-efficacy on the intention to use drones among the millennial cohorts in the study. Together, the research contributes new evidence to empirical research on drone acceptance by highlighting that while self-efficacy may not directly contribute to intentions to use, it nevertheless influences through positive attitudes towards drone delivery. This finding further validates the importance of attitudes on behavioural consequences and in this case, intentions to use drones (Ajzen, 1991; Chen and Hung, 2016; Hwang et al., 2020).

Second, the results highlight the importance of lifestyle compatibility for technology adoption (Rogers, 1995). Lifestyle compatibility was found to positively affect consumer attitude, desire, and intention to use. Earlier research identified the relevance of the lifestyle compatibility on consumer attitudes (Tsai and Tiwasing, 2021) and ultimately, the intention to adopt technologies such as internet and mobile banking (Boateng et al., 2016; Hanafizadeh et al., 2014). This study reveals that this relevance extends to drone delivery. Third, in line with MGB and recent approaches (Bagozzi, 2007; Belk et al., 2020), the results emphasize the role of desire for technology acceptance. Desire is affected by consumer attitude and influences the intention to use. Compared with the extant literature, the above finding contrasts with prior studies in the Airbnb context where it was found that desire is not strongly influenced by attitude (Yi et al., 2020). At the same time, the authors agree with Belk et al. (2020; 14), according to whom "the global consumer of technology must be seduced into perpetual desire for the next new technological wonder, and that the consumer is a willing participant in this seduction."

This study equally confirms the finding in the Asian context regarding the positive contribution of consumer desire on the intention to use drones (Hwang and Choe, 2019; Hwang and Kim, 2021). Therefore, the innermost motivation on the part of the potential consumer to use drones is an important precursor to its usage intention. Similarly, results from the supplementary analysis indicates that desire, which in this case reflects a strong and personal motivation to use drone, is a facilitating mechanism between attitude and use intention. In conclusion, the research findings provide further verification of the predictive utility of MGB in a novel context, which widens the general scope of comprehension of MGB-related phenomena such as desire in studies on consumer adoption of new and innovative technologies.

For the time being, the current research based on data, disagrees with the dominant literature view regarding the role that risk-related factors, such as delivery risk, play when it comes to the acceptance of emerging technologies. (Chiu et al., 2014; Hong and Cha, 2013; Sah et al., 2020; Zhu, 2019). More specifically, this research draws attention to findings that perceived delivery risk neither diminishes the positive influence of attitude nor the positive influence of individual desire to use. This is in contrast with previous arguments that perceive risk significantly weakens, for example, the positive effect of utilitarian value on behavioural intentions (Chiu et al., 2014). While the current moderating evidence contrasts with previous perceived risk research, it nevertheless aligns with the research in cognitive consistency (Brannon and Gawronski, 2018; Kruglanski et al., 2018; Wicklund and Frey, 1981). According to the cognitive consistency literature, individuals deliberately tend to live in harmony with their cognitions that include thought processes, beliefs, and opinions towards a targeted behaviour. In this instance, intentions to use drone. In perspective, the positive influence of both attitude and desire on intentions to use significantly discredit the belief that drone usage for order delivery is highly susceptible to malfunctions, product damage, and untimely delivery. In fact, past research conducted among respondents from another western market exposes that generally individuals do not consider the use of drones to be risky and further imply they do not hold any negative attitudes toward drone acceptance (Clothier et al., 2015). The research is highly suggestive that delivery risk is not a sufficient barrier to millennial consumers' acceptance of drones. One important interpretation for the above finding is that millennials, unlike other generations, are less risk-averse and thus early adopters of new technologies. Moreover, they tend to be more adventurous and excited about what new technologies offer. In this case, they are generally positive and excited about the idea of using a drone. This suggestion provides opportunity for further research to explore the possibility that generational cohorts, as defined by various age groups, interact with delivery risk regarding (dis)adoption of drones. In conclusion, the research evidence, despite contradicting past studies on perceived risk, has in many ways implicated extant research on the cognitive consistency paradigm. Consistent with this paradigm, the research emphasizes that when consumers hold strong and favourable views, beliefs and/or desire towards a target object, or behaviour, they may overlook certain uncertainties and, in this case, perceived delivery risk.

Lastly, the final contribution, which is empirical in nature, originates from the integration of SCT with MGB and which together explains the 66.1% variation in the intention to use drones and which, when compared to initial efforts on this topic (Aydin, 2019; Khan et al., 2019; Ramadan et al., 2017), appears more informative. This research may initiate a better understanding of the critical factors behind consumer acceptance within the European market context and across the millennial cohorts in the world. By leveraging the PLS predictive toolbox, the research model indicates that the findings of the key criterion variable – intention to use – are robust and may therefore, generalize to an audience of interest to researchers and practitioners.

5.3. Recommendations for practical implications

The study results have several practical implications for firms that target young consumers and consider drone delivery. Specifically, firms must consider the compatibility of drone delivery with consumers' lifestyles. Since lifestyles typically differ across countries or even regions, firms should analyze preferences to shop and receive their products. Various aspects of drone delivery, such as environment-friendliness, reliability, safety, or novelty, require to be stressed or destressed based on their compatibility with young consumers' lifestyles. In this regard, drone delivery advertisements on popular social media outlets can be used to convey compatibility with consumer lifestyles (Hwang et al., 2020; Yoo et al., 2018).

Furthermore, exploration of the compatibility of drone delivery with consumer lifestyles assists firms to identify the suitable market segments.

Firms may attempt to positively affect the outcome expectancy of drone delivery, by accentuating its convenience, quality, and good value for money. The last aspect is particularly important, given that younger consumers have, on average, lower incomes. Drone delivery is expected to reduce costs by lower long-term fuel costs and on-the-job accidents (Bamburry, 2015). However, these cost reductions could differ across product/industry contexts. In particular, the cost advantage is more pronounced in areas such as the delivery of food or medical products, where there are low scale economies, with a high risk of road-traffic accidents per unit delivered. It is also in this industry where the speed and convenience of drone delivery appears appreciated by consumers. In other industries where scale economies are important and the cost of using delivery drones exceeds alternative modes of delivery, prospects of drone usage is less bright (McKinnon, 2016).

According to the findings, the role of delivery risk in moderating the effects of key variables on intention to use is insignificant. This is an important finding as earlier discussions of drone delivery listed a higher possibility of theft or attack as potential problems (Bamburry, 2015; McKinnon, 2016). Firms may therefore, focus more on other concerns that comprise privacy risks identified as one of the key factors that impact intention to use (Khan et al., 2019; Lowry et al., 2017). Other initiatives to spark consumers' desire to use drone delivery include marketing communications emphasis of the novelty and the image of a technologically enhanced future (Belk et al., 2020; Hwang et al., 2020).

5.4. Limitations

This work is subject to several limitations. First, intentions to use drone delivery may not lead to actual behaviour (Wang et al., 2006). Future studies may focus directly on consumer choices rather than intentions. Second, most respondents were Czech. Therefore, the results may not be generalized to others, especially non-European countries. Third, more influential factors on drone use in relation to privacy issues should be considered in future research, especially if additional practical implications are to be derived. The research focuses on the market demand for drone services without consideration of the factors of supply and the characteristics of the environment, including relevant legislation. Consumers in remote regions may benefit more from drone delivery than consumers in urban areas (Coyne and Goodman, 2020). Another crucial factor on the supply is the available technology and its associated costs. Future research should address these issues to improve the understanding of the emergent phenomenon of drone delivery and in so doing, improve its implications for both practice, policymaking, and academic studies.

Funding information

No external funding was received for this study.

Declaration of competing interest

None.

References

Abood, D.H., Conway, T.C., 1988. Health Value and Self-Esteem as Predictors of Wellness Behaviors (Report No. 89-27). U.S. Naval Health Research Center, San Diego.

Ajzen, I., 1991. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process*. 50 (2), 179–211.

Alexander, B., Kent, A., 2020. Change in technology-enabled omnichannel customer experiences in-store. *J. Retailing Consum. Serv*. https://doi.org/10.1016/j.jretconser.2020.102338.

Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: a review and recommended two-step approach. *Psychol. Bull*. 103 (3), 411–423.

Armstrong, G., Adam, S., Denize, S., Kotler, P., 2014. In: *Principles of Marketing*, sixth ed. Pearson Publications, New York, NY.

Aurambout, J.-P., Gkoumas, K., Ciuffo, B., 2019. Last mile delivery by drones: an estimation of viable market potential and access to citizens across European cities. *European Transport Research Review* 11 (30), 1–21.

Aydin, B., 2019. Public acceptance of drones: knowledge, attitudes, and practice. *Technol. So*c. 59, 101180. https://doi.org/10.1016/j.techsoc.2019.101180.

Bagozzi, R.P., 2007. The legacy of the technology acceptance model and a proposal for a paradigm shift. *J. Assoc. Inf. Syst*. Online 8 (4), 244–254.

Bain & Company, 2018. *Customer experience tools - Delivery drones*. https://www.bain.com/insights/customer-experience-tools-delivery-drones/ (accessed 9/3/2020).

Baker-Eveleth, L., Stone, R.W., 2008. Expectancy theory and behavioral intentions to use computer applications. *Interdiscipl. J. Inf. Knowl. Manag*. 3, 135–146.

Baloch, G., Gzara, F., 2020. Strategic network design for parcel delivery with drones under competition. *Transport. Sci*. 54 (1), 204–228.

Bamburry, D., 2015. Drones: designed for product delivery. *Design Manage. Rev* 26 (1), 40–48.

Bandura, A., 1977a. *Social Learning Theory*. Prentice-Hall, Oxford, England.

Bandura, A., 1977b. Self-efficacy: toward a unifying theory of behavioral change. *Psychol. Rev*. 84 (2), 191–215.

Bandura, A., 1986. *Social Foundations of Thought and Action: A Social Cognitive Theory*. Prentice Hall, Englewood Cliffs, NJ.

Bandura, A., 1992. Exercise of personal agency through the self-efficacy mechanism. In: Schwarzer, R. (Ed.), *Self-efficacy: Thought Control of Action*. Hemisphere Publishing Corp, pp. 3–38.

Bandura, A., 2005. The evolution of social cognitive theory. In: Smith, K.G., Hitt, M.A. (Eds.), *Great Minds in Management*. Oxford University Press, Oxford, United Kingdom, pp. 9–35.

Bandura, A., 2006. Toward a psychology of human agency. *Perspect. Psychol. Sci*. 1 (2), 164–180.

Bauer, R.A., 1960. Customer behavior and risk taking. In: Hancock, R.S. (Ed.), *Dynamic Marketing for a Changing World*. American Marketing Association, Chicago, pp. 389–398.

Baur, S., Hader, M., 2020. *Cargo Drones: the Future of Parcel Delivery*. Roland Berger, Munich. https://www.rolandberger.com/en/Insights/Publications/Cargo-drones-The-future-of-parcel-delivery.html.

Belk, R., Weijo, H., Kozinets, R.V., 2020. Enchantment and perpetual desire: theorizing disenchanted enchantment and technology adoption. *Market. Theor*. https://doi.org/10.1177/1470593120961461.

Boateng, H., Adam, D.R., Okoe, A., Anning-Dorson, T., 2016. Assessing the determinants of internet banking adoption intentions: a social cognitive theory perspective. *Comput. Hum. Behav.* 65, 468–478.

Brand, C., Schwanen, T., Anable, J., 2020. 'Online omnivores' or 'willing but struggling'? Identifying online grocery shopping behavior segments using attitude theory. *J. Retailing Consum. Serv.* 57, 102195.

Brannon, S., Gawronski, B., 2018. Cognitive consistency in social cognition. In: Hogg, M. (Ed.), *The Oxford Encyclopedia of Social Psychology*. Oxford University Press, New York, NY.

Chen, C., 2013. Perceived risk, usage frequency of mobile banking services. *Manag. Serv. Qual.: Int. J*. 23 (5), 410–436.

Chen, S.C., Hung, C.W., 2016. Elucidating the factors influencing the acceptance of green products: an extension of theory of planned behavior. *Technol. Forecast. Soc. Change* 112, 155–163.

Chiu, C., Wang, E.T.G., Fang, Y., Huang, H., 2014. Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. *Inf. Syst. J.* 24 (1), 85–114.

Clothier, R.A., Greer, D.A., Greer, D.G., Mehta, A.M., 2015. Risk perception and the public acceptance of drones. *Risk Anal*. 35 (6), 1167–1183.

Compeau, D.R., Higgins, C.A., 1995. Computer self-efficacy: development of a measure and initial test. *MIS Q*. 19 (2), 189–211.

Compeau, D., Higgins, C.A., Huff, S., 1999. Social cognitive theory and individual reactions to computing technology: a longitudinal study. *MIS Q*. 23 (2), 145–158.

Conrad, A.M., Munro, D., 2008. Relationships between computer self-efficacy, technology, attitudes and anxiety: development of the computer technology use scale (CTUS). *J. Educ. Comput. Res*. 39 (1), 51–73.

Cook, K.L., 2007. The silent force multiplier: the history and role of UAVs in warfare. In: *IEEE Aerospace Conference* (Institute of Electrical and Electronics Engineers, Piscataway, NJ), pp. 1–7.

Cox, D.F., Rich, S.U., 1964. Perceived risk and customer decision-making: the case of telephone shopping. *J. Market. Res*. 32–39.

Coyne, C.J., Goodman, N., 2020. *Drones, development, and discovery.* Georgetown J. Int. Aff. https://gjia.georgetown.edu/2020/04/15/drones-development-and -discovery/. (Accessed 14 December 2020).

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* 13 (3), 319–340.

DroneRules, 2021. Regulations: Czech republic (CZ). https://dronerules.eu/en/profess ional/regulations/czech-republic. (Accessed 7 April 2021).

Earl, P.E., 1983. *The Economic Imagination: towards a Behavioural Analysis of Choice*. Wheatsheaf, Brighton.

Franke, G., Sarstedt, M., 2019. Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. *Internet Res*. 29 (3), 430–447.

Galkin, B., 2021. L*&RS Spotlight: Consumer and Commercial Drones - How a Technological Revolution Is Impacting Irish Society*. Oireachtas Library & Research Service, Dublin.

Gefen, D., 2000. E-commerce: the role of familiarity and trust. *Omega* 28 (6), 725–737.

Goasduff, L., 2020. *Why flying drones could disrupt mobility and transportation beyond COVID-19*. https://www.gartner.com/smarterwithgartner/why-flying-drones-could-disrupt-mobility-and-transportation-beyond-covid-19/. (Accessed 6 June 2020).

Hair Jr., J.F., Howard, M.C., Nitzl, C., 2020. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *J. Bus. Res*. 109, 101–110.

Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019a. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev*. 31 (1), 2–24.

Hair, J.F., Sarstedt, M., Ringle, C.M., 2019b. Rethinking some of the rethinking of partial least. *Eur. J. Market*. 53, 566–584.

Han, H., Yoon, H.J., 2015. Hotel customers' environmentally responsible behavioural intention: impact of key constructs on decisions in green consumerism. *Int. J. Hospit. Manag.* 45, 22–33.

Han, H., Meng, B., Kim, W., 2017a. Bike-traveling as a growing phenomenon: role of attributes, value, satisfaction, desire, and gender in developing loyalty. *Tourism Manag*. 59, 91–103.

Han, L., Wang, S., Zhao, D., Li, J., 2017b. The intention to adopt electric vehicles: driven by functional and non-functional values. *Transport. Res. Pol. Pract*. 103, 185–197.

Hanafizadeh, P., Behboudi, M., Koshksaray, A.A., Tabar, M.J.S., 2014. Mobile-banking adoption by Iranian bank clients. *Telematics Inf*. 31 (1), 62–78.

Heerink, M., 2011. Exploring the influence of age, gender, education and computer experience on robot acceptance by older adults. In: *2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI).* IEEE, pp. 147–148.

Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modelling. *J. Acad. Market. Sci*. 43 (1), 115–135.

Herzenstein, M., Posavac, S.S., Brakus, J.J., 2007. Adoption of new and really new products: the effects of self-regulation systems and risk salience. *J. Market. Res*. 44 (2), 251–260.

Hong, I.B., Cha, H.S., 2013. The mediating role of consumer trust in an online merchant in predicting purchase intention. *Int. J. Inf. Manag*. 33 (6), 927–939.

Hsu, M.H., Chiu, C.M., Ju, T.L., 2004. Determinants of continued use of WWW: an integration of two theoretical models. *Ind. Manag. Data Syst*. 104 (9), 766–775.

Huang, C.H., Beatson, A., Lings, I., 2015. The role that cognition plays in attitude formation: an alternative model for the determinants of attitude. *J. Manag. Res.* 7 (3), 85–101.

Hwang, J., Kim, H., 2021. The effects of expected benefits on image, desire, and behavioral intentions in the field of drone food delivery services after the outbreak of COVID-19. *Sustainability* 3 (1), 117.

Hwang, J., Choe, J., 2019. Exploring perceived risk in building successful drone food delivery services. *Int. J. Contemp. Hospit. Manag*. 31 (8), 3249–3269.

Hwang, J., Cho, S.-B., Kim, W., 2019a. Consequences of psychological benefits of using eco-friendly services in the context of drone food delivery services. *J. Trav. Tourism Market*. 36 (7), 835–846.

Hwang, J., Kim, H., Kim, W., 2019b. Investigating motivated consumer innovativeness in the context of drone food delivery services. *J. Hospit. Tourism Manag*. 38, 102–110.

Hwang, J., Kim, J.J., Lee, K.W., 2020. Investigating consumer innovativeness in the context of drone food delivery services: its impact on attitude and behavioural intentions. *Technol. Forecast. Soc. Change.* https://doi.org/10.1016/j.techfore.2020.120433, 120433.

Hwang, J., Lee, J.S., Kim, H., 2019c. Perceived innovativeness of drone food delivery services and its impacts on attitude and behavioral intentions: the moderating role of gender and age. *Int. J. Hospit. Manag*. 81, 94–103.

Im, I., Kim, Y., Han, H.J., 2008. The effects of perceived risk and technology type on users' acceptance of technologies. *Inf. Manag.* 45 (1), 1–9.

Joerss, M., Schr¨oder, J., Neuhaus, F., Klink, C., Mann, F., 2016. *Parcel delivery, the future of last mile*. Travel, Transport & Logistics, McKinsey & Company. https://www.mckinsey.com/~/media/mckinsey/industries/travel%20transport%20and%20logistics/our%20insights/how%20customer%20demands%20are%20reshaping%20last%20mile%20delivery/parcel_delivery_the_future_of_last_mile.ashx. (Accessed 17 March 2020).

Khan, R., Tausif, S., Malik, A.J., 2019. Consumer acceptance of delivery drones in urban areas. *Int. J. Consum. Stud*. https://doi.org/10.1111/ijcs.12487.

Kim, D.J., Ferrin, D.L., Raghav, R.H., 2008. A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents*. Decis. Support Syst*. 44 (2), 544–564.

Kim, J.J., Hwang, J., 2020. Merging the norm activation model and the theory of planned behavior in the context of drone food delivery services: does the level of product knowledge really matter? *J. Hospit. Tourism Manag*. 42, 1–11.

Kim, J.J., Kim, I., Hwang, J., 2021. A change of perceived innovativeness for contactless food delivery services using drones after the outbreak of COVID-19*. Int. J. Hospit. Manag*. 93, 102758.

Kim, T.Y., Dekker, R., Heij, C., 2017. Cross-border electronic commerce: distance effects and express delivery in European Union markets. *Int. J. Electron. Commer*. 21 (2), 184–218.

Klauser, F., Pedrozo, S., 2017. Big data from the sky: popular perceptions of private drones in Switzerland. *Geograph. Helv*. 72, 231–239.

Kock, N., 2015. Common method bias in PLS-SEM: a full collinearity assessment approach. *Int. J. e-Collaboration* 11 (4), 1–10.

Kock, N., 2020. *WarpPLS User Manual: Version 7.0*. ScriptWarp Systems, Laredo, TX.

Kock, N., Lynn, G.S., 2012. Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations*. J. Assoc. Inf. Syst. Online* 13 (7), 546–580.

Koenig-Lewis, N., Palmer, A., Moll, A., 2010. Predicting young consumers' take up of mobile banking services. *Int. J. Bank Market.* 28 (5), 410–432.

Kruglanski, A.W., Jasko, K., Milyavsky, M., Chernikova, M., Webber, D., Pierro, A., di Santo, D., 2018. Cognitive consistency theory in social psychology: a paradigm reconsidered. *Psychol. Inq*. 29 (2), 45–59.

Kuo, Y.-F., Lin, C.S., Wu, C.-H., 2020. Why do people intend to back crowdfunding projects? A perspective on social cognitive theory. *J. Electron. Commer. Res*. 21 (3), 180–196.

Leclercq-Vandelannoitte, A., Aroles, J., 2020. Does the end justify the means? Information systems and control society in the age of pandemics. *Eur. J. Inf. Syst*. 1–16.

Lee, M.C., 2009. Factors influencing the adoption of internet banking: an integration of TAM and TPB with perceived risk and perceived benefit. *Electron. Commer. Res. Appl.* 8 (3), 130–141.

Leon, S., 2018. Service mobile apps: a millennial generation perspective. *Ind. Manag. Data Syst.* 118 (9), 1837–1860.

Leone, L., Perugini, M., Ercolani, A.P., 1999. A comparison of three models of attitude–behavior relationships in the studying behavior domain. *Eur. J. Soc. Psychol*. 9 (2-3), 161–189.

Leone, L., Perugini, M., Ercolani, A.P., 2004. Studying, practicing, and mastering: a test of the model of goal directed behavior (MGB) in the software learning domain. *J. Appl. Soc. Psychol*. 34 (9), 1945–1973.

Liu, C., 2016. Understanding player behavior in online games: the role of gender. *Technol. Forecast. Soc. Change* 111, 265–274.

Lopez-Nicolas, C., Molina-Castillo, F.J., 2008. Customer Knowledge Management and E-commerce: the role of customer perceived risk. *Int. J. Inf. Manag.* 28 (2), 102–113.

Lowry, P.B., Dinev, T., Willison, R., 2017. Why security and privacy research lies at the centre of the information systems (IS) artefact: proposing a bold research agenda. *Eur. J. Inf. Syst*. 26 (6), 546–563.

Luppicini, R., So, A., 2016. A technoethical review of commercial drone use in the context of governance, ethics, and privacy. *Technol. Soc*. 46, 109–119.

Maddux, J.E., Norton, L.W., Stoltenberg, C.D., 1986. Self-efficacy expectancy, outcome expectancy, and outcome value: relative effects on behavioral intentions. *J. Pers. Soc. Psychol.* 51, 783–789.

Martins, C., Oliveira, T., Popovic, A., 2014. Understanding the internet banking adoption: a unified theory of acceptance and use of technology and perceived risk application. *Int. J. Inf. Manag*. 34 (1), 1–13.

McKinnon, A.C., 2016. The possible impact of 3D printing and drones on last-mile logistics: an exploratory study. *Built. Environ.* 42 (4), 617–629.

Mingyuan, L., 2019. Civilian UAV social risk prevention and control and legal supervision. *Admin. Ref.* 8, 44–49.

Nakamura, H., Kajikawa, Y., 2018. Regulation and innovation: how should small unmannedcrewed aerial vehicles be regulated? *Technol. Forecast. Soc. Change* 128, 262–274.

Nel, J., Heyns, N., 2017. The in-store factors influencing the use-intention of proximity mobile-payment applications. *Manag. Dynam*. 26 (2), 2–20.

Ofori, K.S., Anyigba, H., Adeola, O., Junwu, C., Osakwe, C.N., David-West, O., 2021. Understanding post-adoption behaviour in the context of ride-hailing apps: the role of customer perceived value. *Inf. Technol. People*, ahead-of-print. https://doi.org/10.1108/ITP-06-2019-0285.

Osakwe, C.N., Okeke, T.C., Kwarteng, M.A., 2021. Trust building in mobile money and its outcomes. *Eur. Bus. Rev*. https://doi.org/10.1108/EBR-09-2020-0221 ahead-of-print.

Parker, K.A., Ivanov, B., Compton, J., 2012. Inoculation's efficacy with young adults' risky behaviors: can inoculation confer cross-protection over related but untreated issues? *Health Commun.* 27, 223–233.

Parker, K.A., Rains, S.A., Ivanov, B., 2016. Examining the "Blanket of Protection" conferred by inoculation: the effects of inoculation messages on the cross-protection of related attitudes. *Commun. Monogr*. 83, 49–68.

Perera, S., Dawande, M., Janakiraman, G., Mookerjee, V., 2018. *Retail deliveries by drones: how will logistics networks change?* Available at SSRN: https://ssrn.com/abstract=3476824 https://doi.org/10.2139/ssrn.3476824.

Perugini, M., Bagozzi, R.P., 2001. The role of desire and anticipated emotions in goal directed behavior: broadening and deepening the theory of planned behavior. *Br. J. Soc. Psychol.* 40 (1), 79–98.

Perugini, M., Bagozzi, R.P., 2004. The distinction between desires and intentions. *Eur. J. Soc. Psychol.* 34, 69–84.

Piçarra, N., Giger, J.C., 2018. Predicting intention to work with social robots at anticipation stage: assessing the role of behavioral desire and anticipated emotions. *Comput. Hum. Behav.* 86, 129–146.

Raj, A., Sah, B., 2019. Analyzing critical success factors for implementation of drones in the logistics sector using grey-DEMATEL based approach. *Comput. Ind. Eng*. 138, 106118.

Ramadan, Z.B., Farah, M.F., Mrad, M., 2017. An adapted TPB approach to consumers' acceptance of service-delivery drones. *Technol. Anal. Strat. Manag*. 29 (7), 817–828.

Ramayah, T., Cheah, J., Chuah, F., Ting, H., Memon, M.A., 2018. In: P*artial Least Squares Structural Equation Modeling (PLS-SEM) Using SmartPLS 3.0: an Updated Guide and Practical Guide to Statistical Analysis*, second ed. Pearson, Kuala Lumpur, Malaysia.

Ratten, V., Ratten, H., 2007. Social cognitive theory in technological innovations. *Eur. J. Innovat. Manag.* 10 (1), 90–108.

Ren, X., Chen, C., 2020. Model of third-party risk index for unmanned aerial Vehicle delivery in urban environment. *Sustainability* 12.

Ringle, C.M., Wende, S., Becker, J.-M., 2015. *SmartPLS 3.* Boenningstedt: SmartPLS GmbH. http://www.smartpls.com. (Accessed 15 October 2020).

Robinson, C., 2017. Disclosure of personal data in ecommerce: a cross-national comparison of Estonia and the United States. *Telematics Inf.* 34 (2), 569–582.

Roca-Riu, M., Menendez, M., 2019. Logistic deliveries with drones: state of the art of practice and research. In: *19th Swiss Transport Research Conference* (STRC), Monte Verit`a, Ascona. May 15-17.

Rogers, E.M., 1995. *Diffusion of Innovations*. The Free Press, New york, NY.

Sah, B., Gupta, R., Bani-Hani, D., 2020. Analysis of barriers to implement drone logistics. *Intern. J. Logis. Res. Appl*. https://doi.org/10.1080/13675567.2020.1782862.

Schunk, D.H., 2012. Social cognitive theory. In: Harris, K.R., Graham, S., Urdan, T., McCormick, C.B., Sinatra, G.M., Sweller, J. (Eds.), *APA Handbooks in Psychology. APA Educational Psychology Handbook, 1*, pp. 101–123. Theories, constructs, and critical issues.

Sekerka, L.E., Bagozzi, R.P., 2007. Moral courage in the workplace: moving to and from the desire and decision to act. *Bus. Ethics Eur. Rev*. 16 (2), 132–149.

Sheeshka, J.D., Woolcott, D.M., MacKinnon, N.J., 1993. Social cognitive theory as a framework to explain intentions to practice healthy eating behaviors. *J. Appl. Soc. Psychol.* 23 (19), 1547–1573.

Shibin, K.T., Dubey, R., Gunasekaran, A., Hazen, B., Roubaud, D., Gupta, S., Foropon, C., 2020. Examining sustainable supply chain management of SMEs using resource based view and institutional theory. *Ann. Oper. Res*. 290, 301–326.

Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.-H., Ting, H., Vaithilingam, S., Ringle, C. M., 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *Eur. J. Market.* 53 (11), 2322–2347.

Soffronoff, J., Piscioneri, P., Weaver, A., 2016. *Public perception of drone delivery in the United States* (RARC-WP-17-001). https://www.uspsoig.gov/document/public-perception-drone-delivery-united-states.

Stone, R.W., Baker-Eveleth, L.J., 2013. Students' intentions to purchase electronic textbooks. *J. Comput. High Educ*. 25 (1), 27–47.

Straub, E.T., 2009. Understanding technology adoption: theory and future directions for informal learning. *Rev. Educ. Res*. 79 (2), 625–649.

Sun, J., 2014. How risky are services? An empirical investigation on the antecedents andconsequences of perceived risk for hotel service. Int. J. Hospit. Manag. 37, 171–179.

Sun, Y., Yang, C., Shen, X.-L., Wang, N., 2020. When digitalized customers meet digitalized services: a digitalized social cognitive perspective of omnichannel service usage. *Int. J. Inf. Manag.* 54 article 102200.

Suseno, Y., Hudik, M., Fang, E.S., Guo, Z., 2020. Employee attitudes, technological anxiety, and change readiness for artificial intelligence adoption. No. 1. In: *Academy of Management Proceedings, 2020*, p. 20045. Briarcliff Manor, NY 10510: Academy of Management.

Taylor, J.W., 1974. The role of risk in customer behavior. *J. Market*. 54–60.

Teo, T., 2009. Modelling technology acceptance in education: a study of pre-service teachers. *Comput. Educ*. 52, 302–312.

Thusi, P., Maduku, D.K., 2020. South African millennials' acceptance and use of retail mobile banking apps: an integrated perspective. *Comput. Hum. Behav*. 111, 106405.

Tracxn, 2021. *Drones startups in Czech republic*. https://tracxn.com/explore/Drones-Startups-in-Czech-Republic. (Accessed 4 July 2021).

Tsai, Y.-T., Tiwasing, P., 2021. Customers' intention to adopt smart lockers in last-mile delivery service: a multi-theory perspective*. J. Retailing Consum*. Serv. 61, 102514.

Tsiamis, N., Efthymiou, L., Tsagarakis, K.P., 2019. A comparative analysis of the legislation evolution for drone use in OECD countries. *Drones* 3 (4), 75. https://doi.org/10.3390/drones3040075. MDPI AG. Retrieved from.

Urban, Hub, 2018. *Delivering the goods: drone delivery gets off the ground*. https://www.urban-hub.com/technology/delivering-the-goods-drone-delivery-gets-off-the-ground/. (Accessed 12 March 2020).

Veal, A.J., 1993. The concept of lifestyle: a review. *Leisure Stud*. 12 (4), 233–252.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. *MIS Q*. 27 (3), 425–478.

Vijayasarathy, L.R., 2004. Predicting consumer intentions to use on-line shopping: the case for an augmented technology acceptance model. *Inf. Manag*. 41 (6), 747–762.

Wang, Y.S., Lin, H.H., Luarn, P., 2006. Predicting consumer intention to use mobile service. *Inf. Syst. J*. 16 (2), 157–179.

Warshaw, P.R., Davis, F.D., 1985. Disentangling behavioral intention and behavioural expectation*. J. Exp. Soc. Psychol*. 21, 213–228.

Wessels, L., Drennan, J., 2010. An investigation of consumer acceptance of m-banking. *Int. J. Bank Market.* 28 (7), 547.

Wicklund, R.A., Frey, D., 1981. Cognitive consistency: motivational vs non-motivational perspectives. In: Forgas, J.P. (Ed.), *Social Cognition: Perspectives on Everyday Understanding*. Academic Press, London, pp. 141–163.

Wright, D., Finn, R., Gellert, R., Gutwirth, S., Schütz, P., Friedewald, M., Mordini, E., 2014. Ethical dilemma scenarios and emerging technologies. *Technol. Forecast. Soc. Change* 87, 325–336.

Yang, K., 2012. Consumer technology traits in determining mobile shopping adoption: an application of the extended theory of planned behavior. *J. Retailing Consum. Serv*. 19, 484–491.

Yi, J., Yuan, G., Yoo, C., 2020. The effect of the perceived risk on the adoption of the sharing economy in the tourism industry: the case of Airbnb. *Inf. Process. Manag*. 57 (1), 102108.

Yoo, W., Yu, E., Jung, J., 2018. Drone delivery: factors affecting the public's attitude and intention to adopt. *Telematics Inf.* 35 (6), 1687–1700.

Zhu, X., 2019. Segmenting the public's risk beliefs about drone delivery: a belief system approach. *Telematics Inf.* 40, 27–40.

Zhu, X., Pasch, T.J., Bergstrom, A., 2020. Understanding the structure of risk belief systems concerning drone delivery: a network analysis. *Technol. Soc*. 62, 101262