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Research Article

Factors Influencing Technology Acceptance of Drones for Last-Mile Food Deliveries: An Adaptation of the UTAUT2 Model

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As the food delivery sector grows in importance, new delivery modes to address service issues, such as costs, swift delivery, and environmental concerns, are being researched. However, research on drone-based food delivery services is still lacking, especially in the Indian context, which the current study aims to address. The study furthered the UTAUT2 model with additional perceived risk and price sensitivity constructs. Quantitative, cross-sectional data was collected nationwide using convenience sampling through online survey questionnaires. The 323 responses were analyzed using the partial least square-structural equation modeling method. The results identified effort expectancy, social influence, and hedonic motivation as significant predictors of attitude and behavioral intention. In an emerging economy with a vast consumer base, this study may offer a preliminary standpoint for understanding the consumer perspective on drone food deliveries. The findings of this study might be necessary for businesses that deal with food delivery logistics as a point of view to formulate successful strategies.

1. Introduction

Transport systems are one of the main pillars of modern-day commerce. They involve many structural and operational elements and tend to influence our lives directly or indirectly. Drones, the recent entrants for delivery services, were used initially for military operations. Early commercial applications focused mainly on agriculture, surveillance, environmental monitoring, and disaster management (oil spills, forest fires, etc.) [1, 2]. Also known as unmanned aerial vehicles (UAVs), drones are self-propelled devices that are flown without direct human input from within or on the aircraft. Drones are now increasingly used in recreational/educational private flying and for aerial videography in movies and coverage of private/public events [3]. Commercial applications try to take advantage of the UAV technology's cost, efficiency, and safety advantages in addition to its environmental benefits.

India, being one of the world's leading drone buyers (22.5% of global UAV imports), has a steady increase in drone usage forecasted due to stakeholder empowerment across various areas of operations, including agriculture, energy, disaster rescue, delivery, and security to name a few [4]. According to projections by the EY-FICCI Drones report [5], the Indian drone market, which was valued at Rs 2,900 crore in 2022, will increase to Rs 81,600 crore by 2025 and Rs 2.95 lakh crore by 2030. Several positive announcements, including an embargo on drone imports, less stringent drone regulations, and 120 crores worth of production-linked incentives, are enabling drone makers in India to realize the immense potential of the global drone market. In one year (2021 to 2022), the number of drone startups rose by nearly 34 percent, from 157 to 221 [6]. India's private and commercial drone ownership ecosystem has been significantly boosted with the new Drone Rules 2021. The regulations clearly demonstrate the government's intention to relax the previously highly restricted regulations and encourage more people and establishments to buy and operate drones for private and commercial purposes. The main point of the new Drone Rules 2021 is the simplification of the licensing process and associated costs. Due to these new developments, delivery services from restaurants and platforms are carefully investigating the prospect of using drones to make food deliveries.

Urban India has adopted online meal delivery due to changing eating and lifestyle patterns and increased disposable income. Online food delivery gathered significant momentum during the COVID-19 pandemic, providing an ideal solution for delivering restaurant meals to the doorstep during isolation and social distancing [7]. The pandemic has acted as a catalyst in aiding online food delivery services to add several new households to its user base as they offer an effective solution owing to convenience, cost-effectiveness, availability, location, and mode of payment. As a result, these factors arguably influence the consumer's choice and perception of the online food delivery services they choose [8]. Additionally, instant delivery of groceries and essential items through apps offering 10-minute delivery service is becoming increasingly popular in India. One of the leading players, Zomato, intends to enter the 10-minute delivery market through its Zomato Instant app. It is only a matter of time before online food delivery services will get on the bandwagon, and there is no denying that India's 10-minute delivery market is becoming more competitive [9]. Companies have started investigating novel modes like drones for food deliveries, which lowers operational expenses and transportation time while minimizing adverse environmental impact.

Online food delivery entails a breadth of costs owing to the large fleet of delivery vehicles, mostly two-wheelers, aimed at providing higher convenience for the customer. Other social costs include increased CO_2 emissions, road congestion, and worsening road safety [10]. Air pollution is a pressing problem in India as vehicular emissions are a significant source of air pollution in India [11]. Current transportation strategies (deliveries on two-wheelers) do not appear adequate to handle this rapidly changing business and environmental situation effectively. The emphasis on competitive advantages and market positioning based on the logistic services offered must be explored further [12]. The service providers must balance crucial issues with increased client expectations for quicker deliveries, low prices, various ordering options, and ecologically friendly solutions. For successful implementation of drone delivery strategies, gauging user acceptability of this new technology at an early stage may shield the implementing firms from a substantial waste of resources [13]. Prior studies opined that a reduction in perceived risks and better benefit perception positively and significantly influenced consumers' attitudes toward online food delivery [14, 15].

Research on the determining factors of consumer acceptance of drone food deliveries started intensifying from the year 2019. Most of the initial research was concentrated in South Korea and China. The market for online food delivery in India is expected to generate US$33.36 billion in revenue by 2023. By 2027, the market volume is predicted to reach US$73.38 billion, with revenue forecast to expand at a high 21.78% annual rate in the next five years, the CAGR 2023-2027 surpassing the growth rate of most countries in the world [16]. By 2027, 330.8 million consumers are projected to be using the online food delivery service far exceeding most countries except China. Most studies so far employ underpinning theories of the Norm Activation Model [17, 18], Theory of Planned Behavior [19], Value Belief Norm [20], Technology Acceptance Model (TAM) [21, 22], Unified Theory of Acceptance and Use of Technology (UTAUT) [23, 24], and extended UTAUT [25, 26]. Studies on drones as food delivery options are few in the Indian context. Employing TAM, Mathew et al. [27] studied the influence of dimensions of motivated consumer innovativeness, green image, and perceived risk on consumer attitude toward drone food deliveries. Another study by Khalil et al. [28] explored the barriers associated with consumer reluctance to embrace drones for food delivery. The research on the subject is still at a very nascent stage, and the proposed study unfolds the understanding of the topic further through the well-acknowledged UTAUT2 model.

Hence, this paper is aimed at ascertaining the important factors that determine public acceptance of drones as a viable online food delivery option and evaluating the impact of these antecedents on customers' attitudes and intention to adopt the service.

Therefore, we state the following objectives built on the theoretical foundation of the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model [29]:

(1) To identify the key antecedents of intention to adopt drone food delivery services by customers

(2) To examine the extent to which the identified antecedents influence the intention to adopt drone food delivery

The paper is organized as follows: a comprehensive review of earlier research investigations is provided in the following section. Later, research hypotheses are presented. The methodology and results of the structural model analysis are described in the next section. Subsequently, the discussion section is presented, and the summary of findings is given along with the conclusion and implications.

2. Literature Review

2.1. Commercial Drone Usage Scenario in India. In India, commercial drone applications are still at an embryonic stage. Though presently in use in a limited number of public projects, drone applications in the private sector are poised for an exponential rise. During the COVID-19 pandemic, drones were utilized for various nationwide tasks for surveillance, sanitization, temperature monitoring, and public announcements [30]. In 2019, the Ministry of Civil Aviation introduced the Drone 2.0 policy, concentrating primarily on beyond visual line of sight (BVLOS) operations. Recently, the ministry notified more liberalized Drone Rules 2021, to make it substantially simpler for firms to own and operate drones by streamlining a complex certification procedure. As per the new rules, special drone corridors will be established for automated package deliveries. Gabani et al. [31] proposed that hybrid drone-truck models could potentially remedy the operational challenges of the traditional truck-based systems used in logistics and distribution. The Government of India recognizes that, by 2030, the nation can be a drone hub globally and acknowledges that UAVs offer remarkable benefits to all economic sectors, foster employment creation, and expedite economic growth [4, 32].

2.2. Theoretical Foundation and Hypothesis Development. The Unified Theory of Acceptance and Use of Technology (UTAUT) model [33] includes eight different acceptance models such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB) [34], and the Theory of Reasoned Action (TRA) [35]. A more comprehensive model, known as the extended Unified Theory of Acceptance and Use of Technology (UTAUT2), was later developed by Venkatesh et al. [29] to address the critique that the previous one was more deterministic and ignored the individual characteristics of the consumer which led to the addition of variables, namely, habit, hedonic motivation, and price sensitivity, that was proposed to be of significant importance for a person to accept and use new technology [29]. Hence, using UTAUT2 as this research's theoretical foundation was deemed theoretically appropriate. UTAUT2 model has also been extensively used in studying users' usage behavior toward innovative technologies in the context of emerging economies [36]. Further, considering the context of drone food deliveries, the UTAUT2 model was adapted to include additional constructs, which will be outlined and justified in the subsequent sections, leading to the development of a hypothetical model for this research (see Figure 1).

2.2.1. Influence of Performance Expectancy on Attitude toward Drone Food Delivery. Performance expectancy (PE) refers to the extent to which the consumer thinks that using drone food deliveries as a delivery option will offer benefits [33]. PE has been established as a rudimentary attribute measured to find an individual's attitude toward using the new technology [37]. Drawing from the "perceived usefulness" construct of the TAM, PE assumes that people attempt to increase their performance using technology. Prior studies indicate that PE is a significant indicator of user acceptance of new technologies, such as autonomous vehicles for last-mile logistics [38–40]. In fact, in the case of delivery applications, perceived usefulness was more important than ease of use [41]. However, in a few other studies, PE was not correlated with consumers' intention to use drones for parcel delivery [42]. Given the Indian context, it would be valuable to understand if drone deliveries are perceived as more convenient and practical than the traditional alternative, as the sociocultural factors and living conditions are primarily heterogeneous. Hence, we state the first hypothesis as shown below.

H1. Performance expectancy significantly influences attitude toward the use of drone food delivery services.

2.2.2. Influence of Effort Expectancy on Attitude toward Drone Food Delivery. Effort expectancy (EE) can be defined as the degree of easiness related to using the new technology [29]. It is the effort needed to utilize the new system, assess how user-friendly it is, and determine whether or not consumers would find it challenging to use. People have been observed to prefer using user-friendly, adaptable, and helpful technology. EE has been observed to affect the customer's attitude and intention toward adopting the technology [33, 43]. It has been observed to positively affect new technology adaptation in the case of food delivery apps [44], m-commerce [45], and Internet banking adoption [46], to name a few. However, some studies found no significant influence of EE on attitude toward using new technology for automated deliveries [39, 47]. To examine the influence of EE in the Indian context for drone food deliveries, we propose the following:

H2. Effort expectancy significantly influences attitude toward the use of drone food delivery services.

2.2.3. Influence of Social Influence on Attitude toward Drone Food Delivery. Social influence is the extent to which a person perceives that significant people in their lives feel that they should use a particular new technology [33]. Analogous to "subjective norm" of TPB, this construct relies on the social and public image of the customer. Customers are more open to accepting new technology, such as drone/autonomous vehicle parcel deliveries, if family, friends, and/or their social influences use the service and recommend it [17, 39, 48, 49]. Yet, in situations, such as mountain rescue operations [47], SI was not found to be a significant influencing factor. Nevertheless, SI was found to positively impact attitude and user intention in the case of new technology use, such as the usage of AI devices [50] and MOOCs [51]. Therefore, following hypothesis can be proposed:

H3. Social influence significantly impacts the attitude toward the use of drone food delivery services.

2.2.4. Influence of Facilitating Conditions on Attitude toward Drone Food Delivery. Facilitating conditions refer to the extent to which a user has confidence that organizational and technical infrastructure exists to back the usage of the novel system [33]. It is the perception of resources (such as smartphones, apps, landing space, and know-how) and support that is available to perform a task where customers have unrestrained access to information and tools that will enable them to use drones for food deliveries. Earlier research on autonomous vehicles/drones for last-mile deliveries and transport found that FC positively impacted attitude and behavioral intention [39, 49, 52]. Similar findings were reported in other settings, such as drone rescues [47] and 3D printing [53]. Therefore, we put forward the following hypothesis:

H4. Facilitating conditions significantly influence attitude toward the use of drone food delivery services.

2.2.5. Influence of Hedonic Motivation on Attitude toward Drone Food Delivery. Analogous to perceived playfulness or enjoyment, hedonic motivation refers to the pleasure gained from new technology usage [29]. It was added to the UTAUT2 model as an additional construct to capture the emotion of joy and fulfillment of using the latest technology through sensory stimulation, symbolism, or the fun aspect during purchase or usage. Hedonically motivated individuals opt to buy a novel product or avail of a service because of thrill and sensorial gratification [54]. Ferdous and Huda [55] observed that the younger generation often

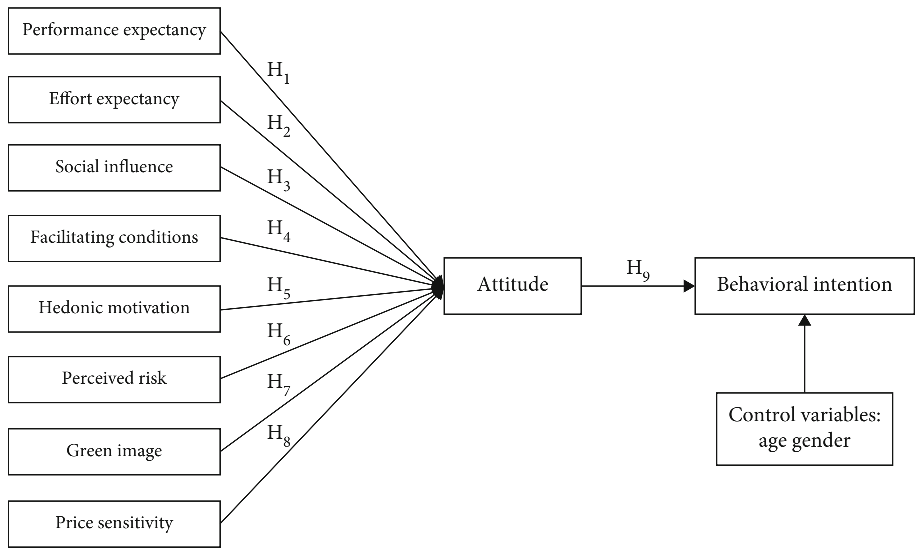

Figure 1: The hypothetical model.

views technology as an experiment to do something enjoyable or fascinating.

Madigan et al. [52] found that HM was a strong predictor of the usage of automated public road transport systems. In many cases, hedonic motivation, seen as a contrast to rationality, was a stronger predictor of new technology acceptance than utilitarian motivation [56]. A positive influence of HM has been observed in prior research regarding drone deliveries/autonomous vehicle deliveries and usage [52, 57, 58]. Features such as hands-free control, gesture recognition, and voice control systems used in drone deliveries seemed to create excitement and fun for the customers [17, 39] to be motivated. However, Mathew et al. [27] found no significant influence of hedonically motivated consumer innovativeness on drone delivery usage intention. Thus, we propose the following:

H5. Hedonic motivation significantly influences attitude toward the use of drone food delivery services.

2.2.6. Influence of Perceived Risk on Attitude toward Drone Food Delivery. As with any new technology, consumers may find it challenging to accept drones for food delivery due to the lack of knowledge and the associated risks. For drone food deliveries, perceived risk is the risk of losses while using drones as a delivery service option [59]. Mathew et al. [27] observed that privacy risk was a concern among young users of drone delivery services, while Zhang et al. [60] found that perceived safety risk adversely influenced attitude by influencing initial trust in the new technology. Most prior studies observed that such perceived risks correlated negatively with attitudes toward drone deliveries [14, 40, 61]. However, a few other studies did not report statistical significance [38, 62, 63]. Zhu et al. [64] opined that malfunctioning of the device, dealing with damaged deliveries, theft of food packages, or individual/buying/location data being misused may be some of the risk concerns that need to be addressed by the delivery firms. Therefore, the following hypothesis is proposed:

H6. Perceived risk significantly affects attitude toward the use of drone food delivery services.

2.2.7. Influence of Price Sensitivity on Attitude toward Drone Food Delivery. In the context of technology acceptance research, price sensitivity refers to how the customers respond to the increases in the prices and charges in adopting the new technology compared to the other traditional methods [65]. Though PS has been used in prior studies, it is still a construct that has received less attention, particularly in technology acceptability and adoption [66]. The significance of delivery expenses has been emphasized by prior research [67], and PS is shown to negatively affect attitude and intention to use a new technology or service, sometimes despite the green image [39, 68–71]. However, it is also observed that millennial customers are not too price-sensitive regarding product attributes and prefer to buy ethically [72]. Therefore, we propose the following hypothesis:

H7. Price sensitivity significantly influences attitude toward the use of drone food delivery services.

2.2.8. Influence of Green Image on Attitude toward Drone Food Delivery. Due to the growing social awareness and pressure for environmental protection, business professionals are more concerned than ever about sustainability. Making consumers adopt ecofriendly services depends mainly on satisfying their environmental needs [73]. Suppose customers are aware of the environmental issues the world is now facing and genuinely believe that it is their responsibility to ease the problem. In that case, they are more likely to buy environmentally friendly products [74]. Customers were willing to pay more for services with an enhanced sense of GI, like drone deliveries [75]. Since they are powered by electricity, drone deliveries have the potential to be an effective delivery method for environmental sustainability when compared to vehicles run on fossil fuels. Greenhouse gas emissions can be lessened due to the lower utilization of resources [76, 77]. In previous studies, GI positively influenced attitudes toward using drone services [17, 27, 40]. Millennials from emerging economies opined that relative advantage and compatibility were deciding factors in adopting green products and services [78]. Thus, we state the following:

H8. Green image positively influences intention toward the use of drone food delivery services.

2.2.9. Influence of Attitude toward Drone Food Delivery on Behavioral Intention. Attitude has been recognized as a strong predictor of intention in several studies [79], especially in the case of online food deliveries [17, 40], post-COVID-19 online food delivery [19, 80], and millennials' online purchasing attitudes and intentions [81]. The relationship was also observed in the case of online food deliveries in the Indian/emerging economy context [15, 82]. Therefore, we propose the following:

H9. Attitude positively influences intention toward the use of drone food delivery services.

2.2.10. Control Variables. Demographics play a vital role in consumers' decisions regarding adopting new products and technologies [83] such as drone technology adoption. Previous research has primarily focused on how demographics, particularly age and gender, influence the acceptance of innovation. It is imperative to delve into the demographic aspect when examining the adoption of drone technology. People tend to be more hesitant about embracing advanced technology as they age. Numerous studies have investigated the role of age and gender as factors that affect, moderate, or serve as control variables [84] in technology adoption research. These studies consistently highlight the significant impact of age and gender on the acceptance of new technologies [85]. Therefore, in this research, we have included age and gender as control variables.

3. Method

3.1. Research Instrument. Data was collected through an online questionnaire survey method. The research instrument was validated, and the proposed hypothetical model (see Figure 1) was empirically analyzed using partial least square-structural equation modeling (PLS-SEM). Since the study's objective was to examine the effect of the influencing factors on attitude and intention, a correlational research design was adopted. The PLS-SEM approach was used for this research to analyze the relationship between the constructs (PE, FC, GI, HM, PE, PR, PS, and SI) and the mediating (AT) and the dependent (BI) constructs. Foremost, the content validation of the research instrument needs to be carried out before evaluating it empirically. Comments and reviews on the questionnaire were sought from two academicians and one industry expert. Minor recommendations related to statement construction and language were incorporated prior to the pilot study phase.

The questionnaire had the following three parts. Following a brief introduction to the study, a link to a three-minute video was provided to equip the participants with some basic idea of drone food deliveries. The link for a 34-second YouTube video on drone food delivery was placed on the first page of the form. The respondents were instructed to click the link and then proceed to the next section on demographic characteristics. The section began with a qualifying question to ascertain if the respondents had watched the video. Only those responses with a yes to the qualifying question were considered for further analysis. Later, participants' demographic characteristics such as age, gender, household income, domicile region, and other characteristics were captured. The third part of the questionnaire had attitudinal questions to measure the various constructs of the hypothesized model (see Figure 1). We used a five-point Likert-type scale ("strongly disagree" (1)-"strongly agree" (5)) for measurement (see Table 1).

3.2. Data Collection. Any research study requires a sampling frame that is thorough, precise, and current. In the absence of such a sampling frame, convenience sampling was used, considering its inherent limitations. By maintaining an audit trail throughout the data-collecting phase and making deliberate attempts to choose samples with homogeneous qualities, care has been taken to assure representativeness and the elimination of bias. The inclusion criteria for the respondents were as follows:

(1) Should be of a minimum 18 years of age (legal age to avail some specific food delivery services)

(2) Should use at least one food delivery service app and should have placed a minimum order of one per month

(3) Should be an Indian national residing in India

The questionnaire was distributed online through emails and on social media. First, a pilot study was conducted to pretest the questionnaire with 25 responses. Later, a larger sample of 331 responses was collected from different parts of the nation, and eight of those responses were discarded from analysis due to straight-lining, unusable, and unintelligible responses. Thus, 323 data points that were complete in every way were utilized for the final data analysis. Table 2 displays the respondents' demographic information. Age-wise, most respondents (56.7%) were in the 18–24 age range; among the 323 respondents, all four regions of the nation were well represented. 75.5% of the sample's population placed more than five online orders per month.

3.3. Statistical Analysis. To test our conceptual model, the partial least square-structural equation modeling (PLS-SEM) method was employed. The measurement model assessment and the structural model evaluation are the two stages of the PLS-SEM analysis process [87]. The first is carried out to assess the validity and reliability of the research instrument, and the second is done to test a hypothesis. The goal of the model estimation in PLS-SEM is to maximize the weighted sum of all correlations, and the method produces a solution that satisfies this maximization condition. A set of linear relationships estimates the relationships between the latent variables of the path model in PLS-SEM.

Table 1: Research instrument.

Research constructs and items		Adapted source
Performance expectancy (PE)		
PE1	"I would find drone food delivery service useful when ordering food."	Venkatesh et al. [29], Araújo Vila et al. [86]
PE2	"Using drone food delivery service will increase my chances of getting on time delivery."	
PE3	"Using drone food delivery service will help me get faster delivery."	
PE4	"Using drone food delivery service will increase my quality of life."	
Effort expectancy (EE)		
EE1	"I think it will be easy for me to learn how to use drone food delivery service."	Venkatesh et al. [29], Araújo Vila et al. [86]
EE2	"I think my interaction with the service via the mobile application will be clear and understandable."	
EE3	"I think I will find interacting with drones easy when using drone food delivery service."	
EE4	"I think it will be easy for me to become skillful at using drone food delivery service."	
Social influence (SI)		
SI1	"People who are important to me will think that I should use drone food delivery services."	Venkatesh et al. [29], Araújo Vila et al. [86]
SI2	"People who influence my behavior will think that I should use drone food delivery services."	
SI3	"People whose opinion I value will prefer that I use drone food delivery services."	
Facilitating conditions (FC)		
FC1	"I think I will have the resources necessary to use drone food delivery service."	Venkatesh et al. [29], Araújo Vila et al. [86]
FC2	"I think I will have the knowledge necessary to use drone food delivery service."	
FC3	"I think Drone food delivery services will be compatible with other technologies I use."	
FC4	"I think I will get help from the service provider if I have any difficulty using the drone food delivery service."	
Hedonic motivation (HM)		
HM1	"Using drone food delivery service will be fun."	Venkatesh et al. [29], Araújo Vila et al. [86]
HM2	"Using drone food delivery service will be enjoyable."	
HM3	"Using drone food delivery service will be entertaining."	
Perceived risk (PR)		
PR1	"Overall, using drone food delivery service will be very risky."	Kapser and Abdelrahman [39]
PR2	"Overall, using drone food delivery service will be very dangerous."	
PR3	"Using drone food delivery service as an option will expose me to overall risk."	
Green image (GI)		
GI1	"Drone food delivery services are more likely to be successful in environmental protection."	Kim and Hwang [17]
GI2	"Drone food delivery services are more likely to be well-established in environmental concerns."	
GI3	"Drone food delivery services are more likely to have a strong environmental reputation."	
Price sensitivity (PS)		
PS1	"I would not mind paying more to try out Drone Food Delivery Service as a delivery option."	Kapser and Abdelrahman [39]
PS2	"I would not mind spending more money for getting my orders delivered by drone food delivery service."	
PS3	"I would be willing to pay for drone food delivery service as a delivery option even if it costs more."	
PS4	"If I knew that drone food delivery service as a delivery option were likely to be more expensive than conventional delivery option, that would not matter to me."	
Attitude (AT)		
AT1	"Using drone food delivery services when ordering food is more likely to be (Unfavorable/Favorable)"	Kim and Hwang [17]
AT2	"Using drone food delivery services when ordering food are more likely to (Bad/Good)"	
AT3	"Using drone food delivery services when ordering food are more likely to (Negative/Positive)"	

Table 1: Continued.

Research constructs and items		Adapted source
Behavioral intentions (BI)		
BI1	"I intend to use drone food delivery service as an option in the future."	
BI2	"I will always try to use drone food delivery services in my daily life."	Venkatesh et al. [29]
BI3	"I plan to use drone food delivery service frequently when available in the future."	

Table 2: Demographic profile of respondents.

Attributes	Frequency	Percentage
Gender		
Male	170	52.6
Female	146	45.2
Prefer not to say	7	2.2
Age group		
18-24	183	56.7
25-34	92	28.5
35-44	13	4
45-54	21	6.5
>55	14	4.3
Education level		
Undergraduate	75	23.2
Graduate	197	61
Postgraduate	47	14.6
PhD	4	1.2
Domicile region		
North India	78	24.1
South India	79	24.5
East India	79	24.5
West India	87	26.9
Online food ordering frequency (per month)		
<5 times	79	24.5
5-10 times	160	49.5
11-15 times	83	25.7
>15 times	1	0.3
Avg. monthly expenditure on food ordered online (Indian rupees)		
<1000	6	1.9
1001-2000	55	17
2001-3000	105	32.5
>3000	157	48.6

When applying the categorical scaling procedure in PLS-SEM, only the correlations between the latent variables are considered [87].

3.3.1. Common Method Bias and Multicollinearity Test. Using the same survey instrument to measure dependent and independent variables could lead to common method bias (CMB). When Harman's single-factor analysis was used to evaluate CMB, the results showed that only 18.9 percent of the total variation can be attributed to a single factor, which is much less than the 50 percent threshold. As a result, it may be considered that the data set does not contain a single dominant element, demonstrating that CMB was not a problem in the sample data that was obtained. The variance inflation factor (VIF) values should be less than 3 for the constructs to ensure that the model is free of multicollinearity issues. Table 3 shows that all the constructs had VIF scores much lesser than the threshold of 3, indicating no multicollinearity issues.

3.3.2. Measurement Model Analysis. Before examining the inferential statistics, the survey instrument's validity and reliability must be evaluated. The questionnaire's convergent validity and discriminant validity were both assessed. Convergent validity can be proved if the average variance extracted (AVE) is larger than 0.50 [87]. The AVE values for three constructs, PE (0.450), EE (0.471), and FC (0.462), were slightly less than the desired cutoff of 0.50. However, all the other constructs had AVE values well above 0.50 (see Table 4). The items with factor loadings less than 0.50 were also removed from the model [88]. Further, all the constructs had composite reliability (CR) greater than 0.70 (see Table 4). Even though the AVE values of a few constructs were slightly less than 0.50, the convergent validity could be established based on higher CR (>0.70) values for all the constructs of the model [88]. Past research [89, 90] considered this criterion for convergent validity. Hence, the model's convergent validity was adequately established.

The discriminant validity was checked using the Fornell-Larcker (FL) criterion and heterotrait-monotrait (HTMT) ratios [87]. All constructs were observed to fulfill the FL criterion (see Table 5). Additionally, HTMT ratios were also observed to be less than the threshold value of 0.90 [87], implying that the model demonstrated acceptable discriminant validity (see Table 6).

3.4. Structural Model Analysis. The structural model is given in Figure 2, and the hypothesis testing findings are shown in Table 7. The latent variable performance expectancy ($\beta = 0.109$, $p < 0.1$), effort expectancy ($\beta = 0.252$, $p < 0.01$), social influence ($\beta = 0.203$, $p < 0.01$), hedonic motivation ($\beta = 0.171$, $p < 0.01$), and price sensitivity ($\beta = 0.147$, $p < 0.05$) were found to have a significant influence on attitude thus confirming hypotheses H1, H2, H3, H5, and H8, respectively. Further, the attitude significantly influenced behavioral intention ($\beta = 0.390$, $p < 0.01$), confirming H9. The constructs that did not significantly influence attitude were facilitating conditions, perceived risk, and green image (Table 7).

Table 3: VIF scores for multicollinearity testing.

Dependent variable: attitude	
Constructs	*VIF*
Effort expectancy	1.455
Facilitating conditions	1.377
Green image	1.304
Hedonic motivation	1.310
Perceived risk	1.348
Performance expectancy	1.674
Price sensitivity	1.534
Social influence	1.148

The control variables considered for this research were age and gender. The influence of the same was also analyzed using multigroup analysis. It was found that hedonic motivation had a significant influence on attitude ($\beta = 0.186$, $p < 0.05$) for the lower age group (18-24 years); the same was found to be not significant for the higher age bands ($\beta = 0.173$, $p > 0.05$). On the contrary, factors such as perceived risk ($\beta = 0.238$, $p < 0.05$), price sensitivity ($\beta = 0.301$, $p < 0.05$), and social influence ($\beta = 0.258$, $p < 0.01$) were found to have a significant influence on attitude for higher age bands (>25 years), but the same was found not to be significant for lower age band (18-24 years). For the rest of the factors, no significant differences were observed between age groups. Further, while analyzing gender, it was found that the influence of price sensitivity on attitude was the only factor that showed a significant difference between males and females. Price sensitivity showed a significant influence on attitude for males ($\beta = 0.185$, $p < 0.05$); however, it was not significant for females ($\beta = 0.144$, $p > 0.05$).

3.5. Model Fit. In a multivariate research model, it is essential to determine the model fit to establish the validity of the results. One of the model fit estimates is the coefficient of determination. The coefficient of determination values (R^2) of the endogenous constructs—attitude and behavioral intention—was calculated as 0.152 and 0.267 respectively. In social science research, an R^2 value greater than 0.10 is acceptable when most explanatory variables are statistically significant [91]. In this research, six out of the nine hypothetical relationships are found statistically significant; hence, the R^2 values are acceptable. Another estimate of model fit is the standardized root which refers to square residual (SRMR) [87], and it should not be greater than 0.080 to be considered normalized. The results showed an acceptable value of 0.069 for the research model. Further, goodness of fit (GoF) was calculated using equation (1) and was found to be 0.346, indicating moderate goodness of fit [92].

$$\mathrm{GoF} = \sqrt{\overline{R^2} \times \overline{\mathrm{AvE}}} = \sqrt{0.209 \times 0.573} = 0.346. \quad (1)$$

3.6. PLSpredict Analysis. The apparent dichotomy between explanation and prediction could be solved by introducing PLS-SEM as a "causal-predictive" method. For aiding future studies, factors can be replaced to be useful for subsequent research, and by keeping the sample, the researchers expect to evaluate the capacity to predict outcomes outside of the sample. This analysis is made simpler by the PLSpredict procedure in PLS-SEM, which generates case-level predictions on an item or construct level using holdout samples [79, 87]. The predict evaluation shows that both attitude (AT) and behavioral intention (BI) have sufficient predictive relevance effects in the model because their resulting predict values are above zero (see Table 8). The predictive relevance of the model for out-of-sample prediction was evaluated using PLSpredict. To demonstrate high predictive power, the PLS-SEM RMSE value should be lower than the LM (linear regression model) RMSE [79, 87]. Considering this, the results can be summed up as follows: attitude and behavioral intention have a high predictive power (see Table 8), further supporting the model's validity.

4. Discussion

Performance expectancy significantly influenced the attitude toward drone usage for food deliveries, in line with many prior studies [38–40]. Our findings also draw parallels with previous studies where functionally motivated consumer innovativeness (fMCI), which can be considered analogous to PE, significantly influenced behavioral intentions [40, 61]. Since food deliveries using drones provide more flexibility regarding location and accessibility, it is believed to be more consumer-oriented functionally than traditional alternatives.

Effort expectancy also significantly positively influenced attitude toward drone food deliveries. The findings on effort expectancy agreed with prior studies by Hwang and Choe [61], Lee et al. [44], and Ozturk et al. [93] but in disagreement with Holzmann et al. [47] and Kapser and Abdelrahman [39], who researched automated vehicles for last-mile deliveries. The result shows that the extra effort needed to transition from conventional food deliveries on motorbikes is vital in determining consumer attitudes toward drone food deliveries. Assurance that the additional effort is minimal might assuage some of the additional effort concerns.

Social influence and hedonic motivation were also seen to have a positive influence on attitude toward drone deliveries in compliance with findings by Kim and Hwang [17], Kim and Chung [48], and Zhou et al. [49] confirming the positive impression of family, friends, and/or social influences on attitude formation. The next decisive factor was hedonic motivation. Perceived as the enjoyment offered by the new technology because of the feelings of excitement and fun, our findings concur with other studies where HM proved to wield a significant influence on attitude [17, 39, 52, 57, 58].

Price sensitivity, captured through questions analogous to the willingness to pay for drone delivery services, was found to have a significant effect on attitude. In an emerging economy like India, consumers are presumably concerned about the possible increase in price when a new technology is offered. Though some differences were found with respect to studies involving the younger generation [72], our results

Table 4: Measurement model results.

Latent variable	Observed variable	Outer loadings	Composite reliability	Average variance extracted
Performance expectancy (PE)	PE2	0.741	0.709	0.450
	PE3	0.591		
	PE4	0.673		
Effort expectancy (EE)	EE1	0.766	0.726	0.471
	EE3	0.602		
	EE4	0.680		
Social influence (SI)	SI1	0.805	0.863	0.678
	SI2	0.811		
	SI3	0.853		
Facilitating conditions (FC)	FC1	0.630	0.720	0.462
	FC2	0.694		
	FC3	0.712		
Hedonic motivation (HM)	HM1	0.685	0.812	0.592
	HM2	0.790		
	HM3	0.826		
Perceived risk (PR)	PR1	0.899	0.868	0.688
	PR2	0.735		
	PR3	0.846		
Green image (GI)	GI1	0.793	0.756	0.512
	GI2	0.568		
	GI3	0.766		
Price sensitivity (PS)	PS1	0.857	0.916	0.732
	PS2	0.824		
	PS3	0.920		
	PS4	0.816		
Attitude (AT)	AT1	0.760	0.819	0.601
	AT2	0.811		
	AT3	0.753		
Behavioral intention (BI)	BI1	0.586	0.776	0.540
	BI2	0.781		
	BI3	0.817		

Note: items PE1, EE2, and FC4 deleted due to low factor loadings (less than 0.5).

agreed with studies that confirmed the significant influence of price sensitivity on attitude [39, 68–71].

Facilitating conditions (FC) were not found to be an influencing factor diverging from the results of Kapser and Abdelrahman [39], Madigan et al. [52], and Zhou et al. [49]. This could also be attributed to the scarce media attention given to drone food deliveries and limited coverage of the required/available infrastructure for deliveries by UAVs and associated routing problems [94]. Ascribable to comparable reasoning, the green image also did not seem to influence consumers' attitudes toward food deliveries using drones, even though previous studies suggest that it impacts attitude [17]. Many food service businesses are working to enhance their green image by providing environmentally tuned products and services to consumers using green packaging efforts, sustainable supply chains, and manufacturing practices. Creating a green image for drone food delivery services by creating awareness is crucial for food delivery businesses to project a green image.

Numerous studies have shown that although the public acknowledged the potential benefits of drone deliveries, they also voiced apprehensions about the associated risks, such as system or equipment failure and privacy risks. However, according to our findings, risk perception did not significantly influence consumers' attitudes. The idea of drone food deliveries was not viewed as particularly unsafe or risky by the respondents. Similar findings were reported in Australia by Clothier et al. [63]. Due to the comparable experiences with other innovative products and services, consumers may be ready to overlook the odd drone delivery

Table 5: Fornell-Larcker criterion.

Latent variable	AT	BI	EE	FC	GI	HM	PE	PR	PS	SI
AT	**0.775**									
BI	0.390	**0.735**								
EE	0.383	0.334	**0.686**							
FC	0.188	0.157	0.472	**0.680**						
GI	0.239	0.193	0.265	0.114	**0.716**					
HM	0.267	0.226	0.227	0.155	0.331	**0.769**				
PE	0.314	0.248	0.333	0.283	0.240	0.285	**0.671**			
PR	-0.097	-0.107	-0.107	0.048	-0.312	-0.333	-0.230	**0.829**		
PS	0.189	0.131	0.135	-0.055	0.162	0.067	0.271	-0.536	**0.855**	
SI	0.318	0.260	0.188	0.052	0.288	0.128	0.252	-0.124	0.143	**0.823**

Note: (1) AT: attitude; BI: behavioral intention; EE: effort expectancy; FC: facilitating conditions; GI: green image; HM: hedonic motivation; PE: performance expectancy; PR: perceived risk; PS: price sensitivity; SI: social influence. (2) Bold diagonal indicates square root of AVE.

Table 6: Heterotrait-monotrait ratio.

	AT	BI	EE	FC	GI	HM	PE	PR	PS
AT									
BI	0.619								
EE	0.699	0.692							
FC	0.346	0.330	0.891						
GI	0.391	0.379	0.544	0.234					
HM	0.391	0.345	0.412	0.295	0.584				
PE	0.589	0.546	0.794	0.696	0.544	0.568			
PR	0.129	0.171	0.197	0.122	0.472	0.434	0.431		
PS	0.226	0.191	0.233	0.100	0.216	0.095	0.448	0.673	
SI	0.442	0.380	0.331	0.209	0.461	0.178	0.478	0.177	0.177

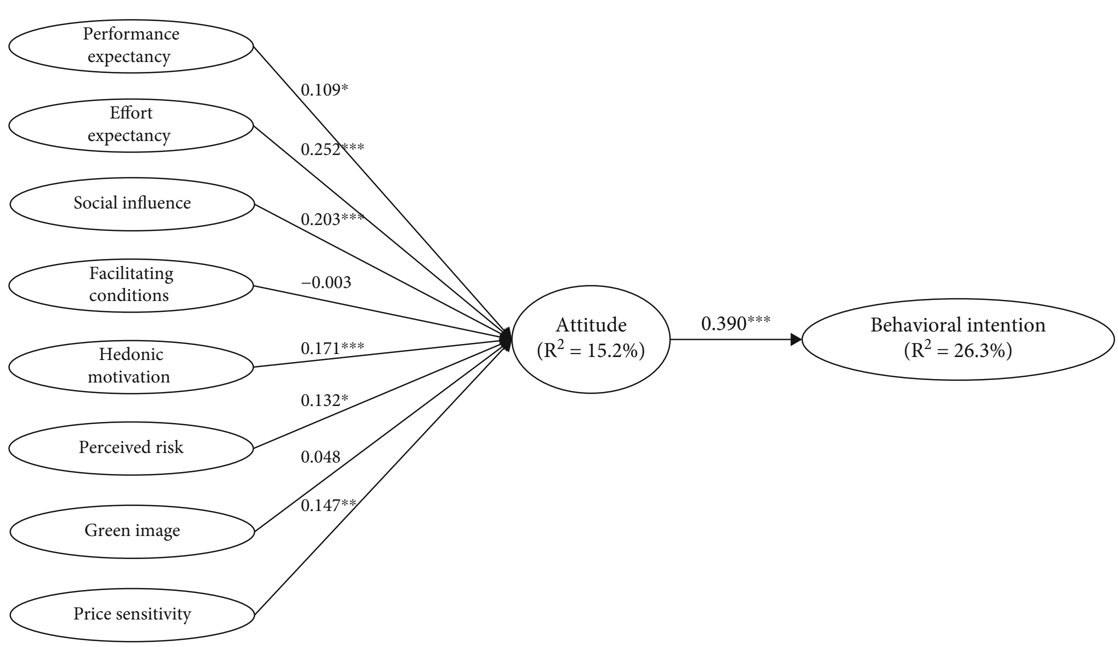

Figure 2: Path model results (note: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$).

Table 7: Hypothesis results.

Hypothesized relationship	β-values	T statistics	p values	Hypothesis result
AT ⟶ BI	0.390	7.475	0.000	Supported
EE ⟶ AT	0.252	4.621	0.000	Supported
FC ⟶ AT	-0.003	0.051	0.959	Not supported
GI ⟶ AT	0.048	0.713	0.476	Not supported
HM ⟶ AT	0.171	3.228	0.001	Supported
PE ⟶ AT	0.109	1.852	0.064	Supported
PR ⟶ AT	0.132	1.555	0.120	Not supported
PS ⟶ AT	0.147	2.118	0.034	Supported
SI ⟶ AT	0.203	3.753	0.000	Supported

Table 8: PLSpredict.

Items	Q^2 predict	PLS-SEM (RMSE)	LM (RMSE)	PLS-SEM-LM (RMSE)	Interpretation
AT1	0.123	0.427	0.444	-0.017	
AT2	0.155	0.471	0.490	-0.019	High
AT3	0.136	0.501	0.522	-0.021	
BI1	0.050	0.496	0.519	-0.022	
BI2	0.075	0.608	0.645	-0.037	High
BI3	0.084	0.530	0.550	-0.020	

Note: high: PLS < LM for all the items; medium: PLS < LM for most items; low: PLS < LM for a minority of the items.

mishaps and treat them as early hitches that they may believe to be a part of new technology. Finally, like numerous previous studies, our results also showed a significant influence of attitude on consumer behavior [15, 17, 40, 82].

5. Conclusion

This study investigated the elements that affect customers' attitudes and behavior decisions toward acceptance of drone food deliveries using the UTAUT2 model. Based on their relative significance, the study advises food delivery service providers to take into account these five key determinants of behavioral intents when developing strategic planning for encouraging customers to favor drone delivery services for food parcels, namely, performance expectancy, effort expectancy, hedonic aspects, price sensitivity, and social influences. Although there have been some studies on the usage of drones for food deliveries in developed nations, this is one of the few to examine the impact of such methods in India. In this emerging economy, the rise of online food deliveries over the last few years has been phenomenal. Due to the immense population and ever-expanding middle-class consumer base, India may be considered a pertinent representative of these nations. Several implications can be drawn from the findings for academics and practitioners involved in online food deliveries.

6. Implications of the Study

6.1. Theoretical Implications. This study attempts to make an important contribution to understanding the factors influencing drone food delivery user acceptance in a populous country like India, where studies related to the topic are scarce. This study adds to the academic literature on drone delivery logistics by being the first to use the UTAUT2 model in the unique cultural milieu of India using post-COVID-19 data. One of the proximate studies on the topic was by Mathew et al. [27], but it was limited to pre-COVID-19 data from university students and used a combination of TAM-TPB models. Since the pandemic outbreak, customers have been sensitized to safe and hygienic practices, and the demand for contactless services only increased. Secondly, price sensitivity, an unexplored factor so far, was included to adapt the model to address the prevalent heterogeneous individual economic status. Price sensitivity influenced the acceptance of drone food delivery options significantly negatively. The study investigated conducive and deterring factors and found that hedonic factors, effort expectancy, and social influence play a pivotal role in technology acceptance. Though the green image was shown to have no significant influence, instead of interpreting these findings conclusively, factors such as awareness of the green benefits of drone deliveries and moral norms may be further investigated. Hence, this study augments the academic literature in the area of technology acceptance and usage of drones for food delivery, especially contributing to the reflections in the context of the emerging nation.

6.2. Practical Implications. This research makes several contributions from a practical standpoint. First, price sensitivity was a decisive factor in user acceptance of drones for food deliveries. Therefore, to convince potential consumers, food delivery firms need to ensure that the price of drone deliveries will be lower than the current method of deliveries using two-wheelers. Advertising must highlight the drone's cost-effective and efficient delivery services to customers to create a favorable perception. Suppose an offer of a better price is impractical. In that case, food delivery companies may have to find a middle ground by initially offering differential pricing to segments likely to bear the burden of a premium cost to avail of drone food delivery services. The marketing units may also begin with trial deliveries to select customers in places like high-end tourist resorts and golf courses.

This study also found that effort expectancy is also important to potential users. Hence, the firms must convey the convenience of drone deliveries over traditional methods through effective marketing campaigns. Companies should underline the ease of operation, convincing through marketing efforts that drone deliveries do not require additional skills and can be used by customers irrespective of their technical knowledge levels. Since hedonic factors were also found to be a significant factor, the features of drones used for deliveries can be made fun and entertaining to use so that consumers think of it as a creative food delivery option. Food delivery companies may develop campaigns showing the new technology's fun aspect. As suggested by earlier researchers, a camera relaying the live real-time images of the delivery route may add a sense of excitement among customers. Such a measure may also act as a deterrent to drone theft and ensure safe food deliveries. In order to highlight the performance aspect of the new method, an advertising strategy that highlights the benefits of drone delivery over the currently used two-wheeler deliveries may be used by businesses to showcase the efficiency of drone food delivery services. Consumers can be made aware of the speed and precision of drone delivery, thereby reducing delays considerably. Customers can also preorder food while moving, another practical benefit of drone food delivery services. Customers may understand the advantages of drone food delivery services through a comparative advertising strategy that emphasizes drone delivery's benefits over conventional methods. The study's findings also indicate favorable social influence to increase the intent to use drones for food deliveries. User-generated content (UGC) may be used to convalesce public opinion by employing customers to participate in drone food delivery promotion. For instance, offers of incentives/coupons to patrons who voluntarily post positive reviews of their food delivery experiences on social media may improve public view of the new technology.

The government's decision to permit drone use for commercial purposes is a positive development. However, the policies and regulations are important in improving drone technology to appeal to industry and the general public. The government would need to encourage and support startups and ventures that want to develop this technology indigenously. This would make it possible to offer drone delivery/logistic services for a reasonable price. The government must create stringent policies to address data theft and other privacy-related concerns.

7. Limitations and Future Scope

Drone food delivery services are still in the trial stage and have yet to be commercialized for public use. Hence, the main limitation of the current study is that the respondents did not have any actual exposure or experience with drone deliveries. Future studies may, therefore, consider studies where the services are available in reality, and consumers are sensitized to drone deliveries through some trials/interactive experiences. Secondly, though care was taken to reduce predisposition, convenience sampling retains some selection bias. Thirdly, since a cross-sectional study was carried out for this research, it does not capture the changing consumer behavior and preferences related to new technology, such as drone food delivery, which could be addressed using a longitudinal research design. Another drawback of the current study is that despite attempts to collect responses from the elderly population, the sample has predominantly respondents aged 18 to 34, which might have played a role in the observed findings. Future studies may consider adequate responses from the elderly population to have an equitable representation of the general population that could potentially use drone food delivery services.

Furthermore, there are many other influencing factors and constructs, and this study only tries to understand attitude through a few limited constructs. Future studies may attempt to widen the investigation by including new factors and other guiding theories. Disruptive technology such as drone deliveries is bound to have many consumer concerns that may not be satisfactorily captured using quantitative studies alone. Moreover, qualitative studies using interviews and focus group discussions may help provide a comprehensive understanding of how each factor influences consumer attitude and intention by thoroughly interpreting the decision-making process, offering more precise insights, and contributing fresh research directions.

Data Availability

Data is available upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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