



Article

Attitude towards Drone Food Delivery Services—Role of Innovativeness, Perceived Risk, and Green Image

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Abstract: The possibility of drone usage for food delivery is met with enthusiasm by businesses as it promises instantaneous benefits such as reduced costs, improved customer satisfaction, and reduced environmental imprint. The objective of this paper is to explore consumer attitude and intention towards adopting a disruptive technology such as drone food delivery in the Indian context through motivated consumer innovativeness (MCI), green image, and perceived risk. We analyzed the questionnaire survey data collected from 310 respondents using structural equation modeling—partial least squares method. Functionally motivated consumer innovativeness and cognitively motivated consumer innovativeness were found to be significant positive predictors of consumer attitude and intention. Perceived privacy risk was found to have a significant negative influence on attitude. Green image had a significant positive effect on attitude towards drone usage. Other components of MCI namely, hedonic and social as well as performance and delivery risk did not show a significance influence. This study, to our knowledge, is first of its kind in India, a populous country with an established and booming economy, where the enabling and impeding antecedents of drone food delivery usage intention is simultaneously studied. The findings of this research will mainly benefit food delivery companies in framing successful drone food delivery strategies.

Keywords: drone food delivery; drone usage; motivated consumer innovativeness; perceived risk; green image



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1. Introduction

Unmanned aerial vehicles (UAV), popularly known as ‘drones’, are defined as: “an aircraft that is operated without direct human intervention from within or on the aircraft” [1]. Though drones were initially developed for military operations, such as surveillance and spying, various businesses have been exploring the possibility of using drones for civilian purposes in the past few years. Currently, drones are increasingly employed in agriculture, rescue activity, firefighting, and rescue activity, to name a few [2]. Furthermore, there has been a continuous growth and rapid increase in UAV technology in recent times [3]. According to the Stockholm International Peace Research Institute’s (SIPRI) arms transfer database, India is one of the top importers of drones accounting for 22.5% of the world’s total UAV imports [4]. Due to the empowerment of stakeholders across different areas of operations including but not limited to agriculture, energy, disaster management, deliveries, GIS, and security, the Ministry of Civil Aviation predicts progressive increase in density of drone usage in the Indian airspace [5]. Though these numbers correspond to the use of drones for military purposes, commercial drones are showing healthy growth. Technology and digitalization has continued to test all technologies and systems in ways that were previously unimaginable. To match this transformation, the government needs to focus on efforts to overcome the obscurity of making economy-impacting decisions with limited information by creating governance structures through policies for a technology

such as drone use [6]. For military, commercial, and business usage of drones, there to leverage the cost, efficiency, and safety benefits of the UAV technology in addition to environmental advantages.

Due to changing lifestyles and eating habits, combined with busy work schedules and a rise in disposable income, urban India has embraced online food delivery services. The convenience of ordering online connected with the food delivery service providers' enticing service has resulted in a consistent increase in the user base, particularly in tier 1 and tier 2 cities. The market for online food delivery is expected to reach \$12.53 billion by 2023, with a growth rate of 15% compared to a 9.01% global average [7]. On the other hand, the unprecedented demand for food delivery services corroborates with the negative environmental impact that the climate scientists are cautioning about. Emerging economies also seem to be on a path where service production and consumption will exceed manufacturing and as a result, may dangerously match or surpass the ecological damage attributed to the latter [8]. Businesses generally tend to prioritize profits over ecological damage unless there are stringent regulations in place and the penalties for violation are severe. However, some companies take steps to proactively test and implement strategies to reduce environmental harm as it also offers competitive edge and financial advantage.

Companies have begun to explore innovative technologies like drones for parcel delivery which reduces the cost and time required for delivery and, at the same time, reduce negative environmental imprint. The Drone 2.0 policy by the Union Civil Aviation Ministry of India in 2019, primarily focusses on Beyond Visual Line of Sight (BVLOS) operations. This new policy has resulted in restaurant-to-delivery (Domino's, KFC, Pizza Hut, etc.) and platform-to-consumer (Swiggy, FreshMenu, Zomato, etc.) delivery companies to intently explore the possibility of drone deliveries. Zomato's acquiring of TechEagle Innovations [9] and subsequent successful testing of drone-based food delivery and the recent legislation regarding commercial use of drones the Indian government has paved the way for the onset and upsurge of this prospect. Hence, there is an urgent need to study the perceptions of prospective customers' benefits and risks towards this emerging technology. This would enable foodservice companies to formulate efficient strategies for marketing before launching it.

This study uses motivated consumer innovativeness (MCI) to examine the influence of functional, hedonic, cognitive, and social motivations on consumer intention formation and innovativeness behavior. A high MCI is indicative of a higher likelihood of consumer acceptance of new technology. Perceived risk, like MCI, is often used in conjunction with the TAM theory to study consumers' attitudes and behavior. Emanating from inadequate knowledge about the functioning of a new technology product or service such as drone delivery, consumers may perceive risk because of ambiguity or a lack of credence.

Air pollution is an imminent and critical concern as 21 of the world's 30 cities with the worst air quality cities are from India [10]. With significant players serving over a million customers per day, mostly in cities, environmental pollution is a significant concern since gasoline-fueled motorbikes are extensively used for food deliveries. Drones can play a vital role in reducing environmental impact as they are operated through batteries and do not emit obnoxious pollutants in the air, unlike the traditional motor vehicles currently used [11].

Hence, we propose to examine the influence of MCI, green image, and perceived risk on consumer attitude and behavioral intention in the context of drone food deliveries. This study would provide a useful basis to understanding consumer perspective on drone food deliveries in the setting of an emerging and densely populated nation like India, which to our knowledge, has not been attempted until now.

In this regard, we propose the following objectives:

1. To examine the impact of MCI, specifically, functional, hedonic, cognitive, and social, on the attitude and behavioral intention of using a drone food delivery service.
2. To analyze the effect of the green image of drone food delivery services on consumers' attitude and behavioral intention towards using this new technology.

3. To investigate the impact of perceived risk, namely, performance, delivery, and privacy risk, on the attitude and behavioral intention of using a drone food delivery service.

The article is structured as follows: a comprehensive review of the insights from previous research studies are presented in the next section. Later, in Section 3, several hypotheses are put forward. The Method section describes the methodology and the key findings of the structural model analysis. In the Discussion section, the results are compared with other research studies and, in the Conclusion and Implications section, the summary of results along with theoretical and managerial implications are outlined. Finally, the limitations and the future scope of the study are conveyed.

2. Literature Review

2.1. Drone Usage—Promising Mode for Food Delivery

Although initially developed for use in military activities such as surveillance and spying, drones have captured various establishments' interest as a promising option for parcel/ food delivery. The key benefits drones offer over traditional modes are speed and on-time deliveries. Drones can operate unaffected by road conditions and traffic congestion and can employ optimum delivery routes, thus reducing delivery costs and time [12,13]. Another significant impact of drone delivery is its environmental impact as it relies on clean energy for its operations rather than gasoline fuels. Simulation studies demonstrate that drone deliveries are more eco-friendly in comparison with their gasoline fueled counterparts [14].

In India, currently, both the drone industry and its market size are at an embryonic stage. However, the drone industry has a vast scope for its exponential rise and growth. The National Highway Authority of India has deployed drones, with the help of Indian start-ups, for 3D digital mapping for detailed project report (DPR) to widen roads for Raebareli-Allahabad Highway [15]. Because of drones' cost-effectiveness, the PGCIL (Power Grid Corporation of India Limited) has employed drones for project monitoring in hilly terrains [15]. Drones are being used by Indian Railways for overseeing and 3D mapping of railway lines' construction on the anticipated project of a 3360 km network of dedicated freight corridor [16]. As commercial drone usage increases in the near future, organizations employing this innovation need to be attentive and cognizant not only to the "drone potential but also to potential drone threat" [17]. Since drone food delivery is a new and unknown service technology, public apprehension, and concern about the safety is quite natural. In fact, it was found that even in the case of activities such as crowd management, search and rescue and policing, socio-demographic differences in the public support for drone usage was observed [18]. Over a period of time, as technology matures and finds ways to be safe and cost-effective, drone usage may find acceptance among a large number of users. Hence, it becomes imperative to the government to frame rules and policies to govern its application and usage.

In 2019, the Union Civil Aviation Ministry of India announced Drone 2.0 policy, focusing primarily on beyond visual line of sight (BVLOS) operations. Online food delivery companies using both restaurant-to-delivery (Domino's, KFC, Pizza Hut, etc.) and platform-to-consumer delivery model (Swiggy, FreshMenu, Zomato, etc.) are now intently exploring the possibility of drone deliveries.

2.2. Motivated Consumer Innovativeness (MCI)

The tendency to buy a new product or a service as soon as it hits the market ahead of other consumers is referred to as consumer innovativeness. Furthermore, motivations energize and encourage this goal-oriented consumer buying behavior [19]. The internal and external elements that lead to consumers' innovative buying behavior are described as MCI [2]. To understand the consumers' attitude and behavior towards a new technology, researchers often employ the motivated consumer innovativeness scale (MCIS) with its four constituents—namely, functionally motivated consumer innovativeness (fMCI), he-

donically motivated consumer innovativeness (hMCI), cognitively motivated consumer innovativeness (cMCI), and socially motivated consumer innovativeness (sMCI) [2,20].

The technology acceptance model (TAM) theory introduced by Davis in 1989 is widely used to assess the consumers' attitude and behavioral intentions towards a new technology [2]. TAM theory is often extended to understand and evaluate the acceptance of technology by consumers, which means that even after the repeated substantiation of TAM theory exceedingly in different fields, many researchers have priorly tried to extend TAM by incorporating additional parameters [21–23]. The two main drivers that constitute TAM—namely, perceived usefulness and perceived ease of use—are closely associated with fMCI and cMCI, respectively [24]. Apart from measuring the fMCI and cMCI, this study also focused on hedonic (hMCI) and social aspects (sMCI) of consumer motivation, which altogether forms the basis of the MCI model [2].

Firstly, fMCI refers to “consumer innovativeness motivated by the functional performance of innovations and focuses on task management and accomplishment improvement” [2]. Functional motivation towards an innovative product/service results from consumers' need to ameliorate their performance or organization, to enhance and accelerate their productivity [20]. The functionally motivated consumer tends to buy a product because of its utilitarian values. Next, hMCI can be defined as “consumer innovativeness motivated by affective or sensory stimulation and gratification” [2]. “Hedonically motivated consumers” buy a product/service based on a new technology because of the feelings of excitement, fun, playfulness, and satisfaction stimulated in their senses by using the product/service [19]. Next, cMCI refers to “consumer innovativeness motivated by the need for mental stimulation” [2]. Cognitively motivated consumers buy innovative products to expand and challenge their mental ability. They are inclined towards exploring, understanding, and intellectual creativity [19]. Lastly, sMCI can be defined as “consumer innovativeness motivated by the self-assertive social need for differentiation” [2]. Social motivation towards an innovative product results from consumers' need to establish and maintain a social relationship [20]. Consumers often buy a new technology-based product to flaunt among their peers in society as it makes them feel unique, special, or free. Also, it helps them to acquire a social status/superiority among others and be socially distinguishable [19].

2.3. Green Image

The green image is defined as “consumers' perceptions of a brand (firm) that is solely linked to environmental commitment and environmental concerns” [25]. The alarming rise in global warming and environmental pollution is regarded as a significant problem in today's world, leading to an increased effort to combat this crisis [26]. Because of the consumers' increasing concern about environmental issues, many researchers emphasize the preeminence of green image rather than the organization's overall image to attract environmentally conscious consumers. Consumers who are aware of the environmental issues the world is facing today and genuinely consider it their responsibility are more likely to purchase environmentally friendly products [27]. Since green decisions often affect their immediate environment, consumers may be willing to pay extra for services with an elevated perception of a green image, such as drone deliveries [28]. To appeal to such consumers, organizations need to focus on building a green brand image. These customers regard such an image as an important selection criterion while buying/using products/services [11].

Experimental studies have time and again corroborated the relevance of green image in shaping the customer attitude and consequently their behavioral intentions. It is understood that if consumers perceive an elevated level of a green image from drone food deliveries, they are more likely to have a positive attitude towards using the service [11]. It is found that when compared to rudimentary eco-friendly practices, advanced green practices, such as drone deliveries, are likely to have more significant influences on customer satisfaction and attitude [29–31].

2.4. Perceived Risk

Perceived risk is often used in conjunction with the TAM theory to study consumers' attitude and behavior. It is defined as the "potential for loss in the pursuit of the desired outcome of using an e-service" [32]. Consumers may perceive risk in a new tech-based product/service because of ambiguity or a paucity of credence.

In this study, three types of risks—performance risk, delivery risk, and privacy risk—in the context of drone food delivery services are examined. 'Performance risk' is defined as: "possibility of the product malfunctioning and not performing as it was designed and advertised and therefore failing to deliver the desired benefits" [32]. Consumers are also concerned that the parcel might not be delivered to them due to an accident or damage or theft of a drone carrying the food parcel, referred to as the 'delivery risk'. The authorization of civilian drones for commercial use such as food deliveries poses several risks to the privacy and security of people around as drones can easily be used wrongly for surveillance, cyber spying, and snooping into an individual's private and personal data which is termed 'privacy risk' [33].

Risks related to drone usage for civilian purposes may hinder them from accepting them as a mode for food parcel deliveries [34]. Ramadan et al. investigated the effect of privacy risk and safety risk factors on consumers' acceptance of drone food delivery services [33]. Clothier et al. observed that people had a neutral risk-related response in Australia, which suggests that the ordinary public is yet to form an opinion on drone usage for food deliveries [35]. Public knowledge through industry communication and media is likely to influence public perception associated with risks associated with drone food deliveries. Government regulatory laws protecting personal privacy may mitigate these risks and enable acceptance of this innovation [36].

3. Hypothesis Development

3.1. Effect of Motivated Consumer Innovativeness on Attitude

Attitude indicates consumers' favorable or unfavorable intention to use a particular innovation. This study proposes to examine the influence of MCI on the attitude of Indian consumers on drone food deliveries. Prior studies, in various contexts, have reported a significant association between MCI and attitude. For instance, hMCI and sMCI were shown to positively influence consumers' attitude towards robot services in restaurants [37,38]. Vandercaetele and Geuens studied the effect of MCI on attitude in the context of cellular phones; the results clearly indicated the role of MCI in shaping customers' attitude [19]. A study conducted by Hwang et al. found that apart from cMCI, the other three types of MCI positively influenced consumer attitude towards drone deliveries [2]. Companies could devise strategies to leverage MCI to gain consumers' confidence as it is closely and positively related to consumer innovativeness [39].

Hence, to examine the influence of MCI on attitude towards drone food delivery in the Indian context, we put forward the following hypotheses:

Hypothesis 1a (H1a). *Functionally motivated consumer innovativeness (fMCI) positively affects attitude.*

Hypothesis 1b (H1b). *Hedonically motivated consumer innovativeness (hMCI) positively affects attitude.*

Hypothesis 1c (H1c). *Cognitively motivated consumer innovativeness (cMCI) positively affects attitude.*

Hypothesis 1d (H1d). *Socially motivated consumer innovativeness (sMCI) positively affects attitude.*

3.2. Effect of Motivated Consumer Innovativeness on Behavioral Intentions

This study also proposes to investigate the effect of MCI on behavioral intentions. Behavioral intentions can be defined as: “a stated likelihood to engage in a behavior” [2]. Consumers with behavioral intentions are more inclined to use/consume a product as the intentions are predecessors to the actual use of the product/service. Vandercsateele and Geuens proved that a direct, positive relationship exists between MCI and the customer’s intention to buy a product [19]. Specifically, in the case of autonomous cars, Leicht et al. found that MCI positively moderates the relationship between performance expectancy (likened to fMCI) and purchase intentions [40]. hMCI was found to have a significant effect on customer attitude in the context of online food delivery services [41]. Various studies on organic food buying, acceptance of e-commerce, adoption of electric vehicles, and online food delivery ordering have demonstrated the influence of consumer innovativeness on purchase intentions [42–45]. Hence, we propose the following hypotheses:

Hypothesis 2a (H2a). *Functionally motivated consumer innovativeness (fMCI) positively influences behavioral intentions.*

Hypothesis 2b (H2b). *Hedonically motivated consumer innovativeness (hMCI) positively influences behavioral intentions.*

Hypothesis 2c (H2c). *Cognitively motivated consumer innovativeness (cMCI) positively influences behavioral intentions.*

Hypothesis 2d (H2d). *Socially motivated consumer innovativeness (sMCI) positively influences behavioral intentions.*

3.3. Effect of Green Image on Attitude and Behavioral Intention

Previous studies have explored the effect of green image on consumers’ attitude towards using the new product or service. Hwang and Lyu established that an airline company’s green image has a positive impact on building up consumers’ attitude towards the company [27]. Likewise, Assaker et al. observed that the hotels in Europe which bore a green image had an indirect positive effect on the guests’ attitude [25].

It is encouraging to note that an increasingly large population is willing to purchase environmentally friendly products [46]. The green image significantly influenced the consumer intention to visit a hotel with eco-friendly practices [47]. Hwang & Kim observed the positive impact of using eco-friendly services like drone-based food delivery on consumer attitude and intention [11]. Based on these studies, we propose the following hypotheses:

Hypothesis 3 (H3). *Green image of drone food delivery services positively affects attitude toward using drone food delivery services.*

Hypothesis 4 (H4). *Green image of drone food delivery services positively affects consumers’ behavioral intention toward using drone food delivery services.*

3.4. Effect of Perceived Risk on Attitude and Behavioral Intention

Many studies have been conducted to analyze the effect of perceived risk regarding an innovative technology on customers’ attitude towards using it. Travelers’ perceived risk in the context of an innovative technology like an electric airplane was found to influence not only attitude but also behavioral intentions. Fostering trust and attitude would significantly elicit technology adoption behavior and intention to pay for the product/ service [30]. Like MCI, the influence of perceived risk towards the adoption of products and services using innovative/ disruptive technology is studied in various contexts such as electric vehicles, internet banking, green purchase intention [48–50].

Despite their future use in numerous areas, public attitudes toward UAVs' police use and monitoring are varied [51]. However, in the context of drone usage for food deliveries, knowledge related to the product could result in higher consumer confidence and possibly mitigate the perceived risks associated with the UAV usage [35]. Lidynia et al. found that risk factors are critical barriers in the public acceptance of drones [34]. Privacy and safety risk seemed to influence consumers' attitudes towards service delivery drones [33]. Hwang and Choe [52] found that the three types of perceived risk—viz., time risk, performance risk, and psychological risk—negatively influence intentions to use drone food delivery services. Given the coronavirus outbreak's current forbidding situation, the COVID-19 norms may play a moderating influence between consumer attitude and behavior [53]. Based on these studies, we put forward the following hypotheses:

Hypothesis 5a (H5a). *Performance risk negatively affects attitude toward drone delivery.*

Hypothesis 5b (H5b). *Delivery risk negatively affects attitude toward drone delivery.*

Hypothesis 5c (H5c). *Privacy risk negatively affects attitude toward drone delivery.*

3.5. Effect of Attitude on Behavioral Intentions

Theories such as the theory of planned behavior (TPB), technology acceptance model (TAM), and theory of reasoned action (TRA) have established the relationship between attitude and behavioral intentions. Numerous empirical studies in the past, using these theories in isolation or combination, have demonstrated the influence of attitude on behavior. For instance, attitude was found to be a significant predictor of student's intention to use e-learning or entrepreneurial intention [54]. Furthermore, in eco-friendly initiatives—such as green hotels, organic apparel, etc.—attitude, rather than concern, was a significant predictor of behavioral intention [55,56]. Based on these arguments, we propose the following hypothesis.

Hypothesis 6 (H6). *Attitude positively affects behavioral intentions.*

Based on the above literatures, a theoretical model was developed for this research which is presented in Figure 1.

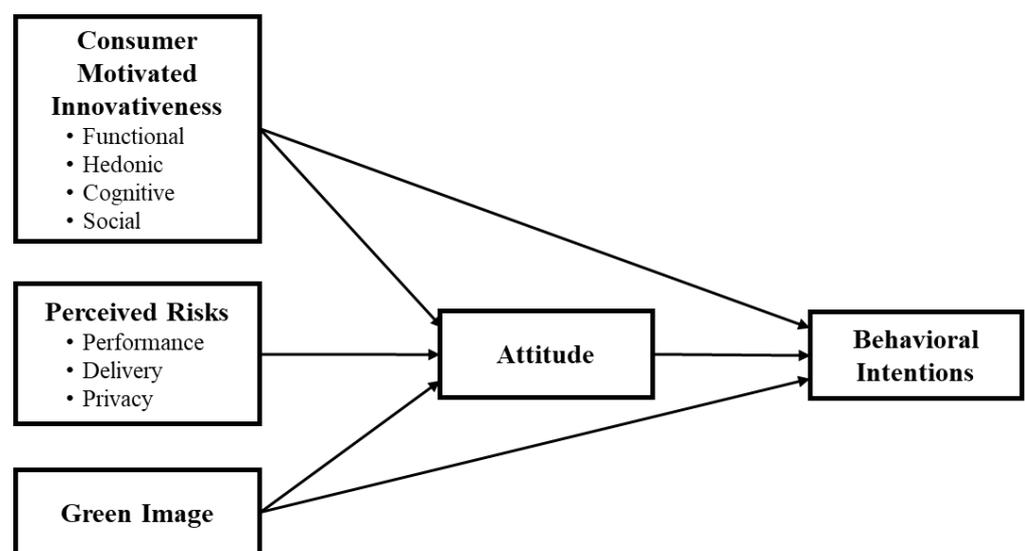


Figure 1. Theoretical model.

4. Method

4.1. Research Instrument

This research follows a quantitative approach, and a questionnaire survey method was used for data collection, which was conducted in the online mode. The measurement model was validated, and the hypotheses were tested using the partial least square-structural equation modeling (PLS-SEM) method. The questionnaire used for this research adopted validated questions from past studies [2,11,32]. Furthermore, experts in the field of marketing and innovation examined the content validity of the questionnaire. Before taking the survey, a short video of approximately 3 min was provided for respondents' perusal if they wanted to understand drone food delivery services' working process. The majority of the questionnaire items (31 items) used a seven-point Likert-type scale ("strongly disagree"(1)—"strongly agree"(7)) for measurement. However, the construct of attitude (three items) was measured using a seven-point bipolar semantic differential scale (Table 1).

Table 1. Research instrument.

Functionally Motivated Consumer Innovativeness (fMCI) ^a	
fMCI1	"Drone food delivery services seem to be efficient."
fMCI2	"Drone food delivery services seem to be convenient."
fMCI3	"Drone food delivery services are likely to shorten the delivery time."
Hedonically Motivated Consumer Innovativeness (hMCI) ^a	
hMCI1	"Drone food delivery services seem to make my life exciting and stimulating."
hMCI2	"It seems to give me a good feeling to use drone food delivery services."
hMCI3	"Using drone food delivery services seems to give me a sense of personal enjoyment."
Cognitively Motivated Consumer Innovativeness (cMCI) ^a	
cMCI1	"I am likely to think logically when using drone food delivery services."
cMCI2	"I am likely to use drone food delivery services after considering various aspects of drone food delivery services."
cMCI3	"I am likely to use drone food delivery services after comparing its advantages and disadvantages."
Socially Motivated Consumer Innovativeness (sMCI) ^a	
sMCI1	"Using drone food delivery services could impress others."
sMCI2	"Using drone food delivery services could show that I am an early adopter."
sMCI3	"Using drone food delivery services could distinguish me from others."
Green Image (GRNI) ^b	
GRNI1	"Drone food delivery services are more likely to be successful in environmental protection."
GRNI2	"Drone food delivery services are more likely to be well-established in environmental concerns."
GRNI3	"Drone food delivery services are more likely to have a strong environmental reputation."
GRNI4	"By using drone food delivery services, I can demonstrate that I care about environmental conservation."
Delivery Risk (DELR) ^c	
DELR1	"The package the drone is carrying might be stolen."
DELR2	"The package the drone is carrying might be damaged by others."
DELR3	"Product delivery may take too long or be incomplete."
DELR4	"It is not easy to cancel orders during delivery."
Performance Risk (PRFR) ^c	
PRFR1	"The drone might malfunction and damage the package it's carrying."
PRFR2	"The drone might malfunction and damage property or injure someone."
PRFR3	"The drone might deliver my package to a different address."
PRFR4	"Flying drones might create a disturbing high-pitch noise."
Privacy Risk (PRVR) ^c	
PRVR1	"Drone delivery will cause me to lose control over my privacy."
PRVR2	"Drone delivery will lead to a loss of privacy for me."
PRVR3	"Drone delivery might not be used in a way that respects my privacy."
PRVR4	"Online retailers may track my shopping habits and history of purchases."

Table 1. Cont.

Attitude (ATT) ^a	
ATT1	“Using drone food delivery services when ordering food is more likely to be (Unfavorable/Favorable)”
ATT2	“Using drone food delivery services when ordering food are more likely to (Bad Good)”
ATT3	“Using drone food delivery services when ordering food are more likely to (Negative/Positive)”
Behavioral Intentions (BHVI) ^a	
BHVI1	“I will use drone food delivery services when ordering food.”
BHVI2	“I am willing to use drone food delivery services when ordering food.”
BHVI3	“I am likely to use drone food delivery services when ordering food.”

Note: Item PRVR3 deleted due to low factor loading. Source: ^a [2], ^b [11], ^c [32].

4.2. Data Collection

Data was collected over three months from the youth population of the Manipal region of Karnataka, India, due to the presence of a diverse youth population from different parts of the country in this region and the prominence of using food delivery services. Manipal is a university town hosting around 30 colleges of various disciplines and having a student population of approximately 25,000. Zomato, the largest Indian online food delivery company, stated that, in its annual report for fiscal year 2019, the city of Manipal has the highest frequency of deliveries in all the 200 cities in which Zomato operates [57]. For these reasons, Manipal was deemed suitable for this study. The convenience sampling method was used for this research, and the questionnaire was circulated in an online mode. Initially, a pilot study was conducted collecting 25 responses to pretest the questionnaire. Later, a larger sample of 317 responses was received from the target population, out of which seven responses were excluded from analysis due to straight-lining and incoherent answering. Therefore, for the final data analysis, 310 responses were used, which were found to be complete in all respects. The demographic details of the respondents are exhibited in Table 2. Most of the respondents (95%) belonged to the age group of 19–24 years, and domicile region-wise, 310 respondents had good representation from all four Indian regions. A significant 41.9% had an online ordering frequency of greater than 10 times in a month among the respondents.

Table 2. Demographic details of respondents.

Attributes	Frequency	Percentage
Gender		
Male	164	53
Female	146	47
Age		
16–18	7	2
19–21	186	60
22–24	108	35
>24	9	3
Domicile Region		
North India	126	40.6
South India	90	29
East India	41	13.2
West India	53	17.1
Online Food Ordering Frequency (Per Month)		
<5 times	83	26.8
5–10 times	97	31.3
10–15 times	66	21.3
15–20 times	29	9.4
>20 times	35	11.2

Table 2. *Cont.*

Attributes	Frequency	Percentage
Avg. monthly expenditure on food ordered online (Indian Rupees)		
<500	67	21.6
500–1000	70	22.6
1000–2000	84	27.1
2000–3000	56	18.1
>3000	33	10.6

4.3. Statistical Analysis

This research used structural equation modeling using the partial least square method for conducting statistical analysis. The tool used for developing the structural model was SmartPLS V3.0. The PLS-SEM approach does not mandate that the data be normally distributed, as this method does not make any distributional assumptions. Complex structural models with reflective and formative measurement models can be easily incorporated in PLS-SEM. This SEM method estimates partial model structures defined in a path model by combining principal components analysis with ordinary least squares regressions. While covariance-based structural equation modeling (CB-SEM) strongly relies on the concept of model fit, this is much less in the case of PLS-SEM [58]. Therefore, considering the sample characteristics, the PLS-SEM approach was deemed suitable for this study. There are two stages of analysis conducted in PLS-SEM—the measurement model evaluation, followed by structural model evaluation. The former is performed to determine the research instrument’s validity and reliability, and the latter for hypothesis testing.

4.3.1. Common Method Bias and Multi-Collinearity Test

Measuring independent and dependent variables using the same survey instrument might result in common method bias (CMB). Harman’s single-factor analysis was performed [59] to assess CMB, and the result of this test revealed that a single factor accounts for only 26.49% of the total variance, which is significantly less than the 50%. Therefore, it may be assumed that there is no single dominant factor in the data set, proving that CMB was not an issue with the sample data collected.

Variance inflation factors (VIFs) measures the collinearity among the constructs in a regression analysis. The VIF values for all the constructs were in the range of 1.253 to 2.172 (Table 3), which were well below the cutoff value of 5 [60]. Therefore, it is safe to assume that there were no multicollinearity issues in the study.

Table 3. Multicollinearity testing—VIF values.

Dependent Variable: ATTD		Dependent Variable: BHVI	
Constructs	VIF	Constructs	VIF
cMCI	1.690	ATTD	1.253
DELR	1.058	cMCI	1.682
fMCI	1.537	fMCI	1.594
GRNI	1.734	GRNI	1.738
hMCI	1.862	hMCI	1.862
PRFR	1.019	sMCI	2.172
PRVR	1.085		
sMCI	2.200		

Note. CR = composite reliability; AVE = average variance extracted; fMCI = functionally motivated consumer innovativeness; hMCI = hedonically motivated consumer innovativeness; cMCI = cognitively motivated consumer innovativeness; sMCI = socially motivated consumer innovativeness; GRNI = green image; PRVR = privacy risk, ATTD = attitude, BHVI = behavioral intention.

4.3.2. Measurement Model Analysis

The validity and reliability of the survey instrument need to be assessed before analyzing the inferential statistics. Both convergent and discriminant validity of the

questionnaire were examined. If the average variance extracted (AVE) is greater than 0.50, and the outer loadings of each item of a construct are more than 0.70 [58] convergent validity can be established. Upon evaluation of the measurement model results, both this criterion was found to be satisfied. The constructs' AVE values ranged from 0.727–0.870, and outer loadings of items were in the range of 0.749–0.950 (Table 4). Therefore, the model's convergent validity was established, which meant a good agreement between two or more items measuring the same construct. Two measures of reliability—Cronbach's alpha and composite reliability (CR) were estimated. Both the reliability statistics for all the latent variables of the study were found to be above the recommended value of 0.70 (Table 4). Consequently, it can be inferred that all the constructs are consistent and highly reliable.

Table 4. Measurement model analysis.

Items	Loadings	Cronbach's Alpha	CR	AVE	Sqrt of AVE
fMCI1	0.919	0.829	0.898	0.747	0.864
fMCI2	0.914				
fMCI3	0.749				
hMCI1	0.920	0.914	0.946	0.854	0.924
hMCI2	0.929				
hMCI3	0.923				
cMCI1	0.771	0.818	0.893	0.736	0.858
cMCI2	0.932				
cMCI3	0.863				
sMCI1	0.880	0.888	0.930	0.815	0.903
sMCI2	0.927				
sMCI3	0.900				
PRVR1	0.856	0.816	0.888	0.727	0.853
PRVR2	0.896				
PRVR4	0.803				
GRNI1	0.879	0.891	0.924	0.754	0.868
GRNI2	0.887				
GRNI3	0.886				
GRNI4	0.819				
ATTD1	0.911	0.925	0.953	0.870	0.933
ATTD2	0.937				
ATTD3	0.950				
BHVI1	0.922	0.924	0.952	0.868	0.932
BHVI2	0.939				
BHVI3	0.933				

Note. CR = composite reliability; AVE = average variance extracted; fMCI = functionally motivated consumer innovativeness; hMCI = hedonically motivated consumer innovativeness; cMCI = cognitively motivated consumer innovativeness; sMCI = socially motivated consumer innovativeness; GRNI = green image; PRVR = privacy risk, ATTD = attitude, BHVI = behavioral intention.

Discriminant validity is used to measure whether the indicators of one construct, which are not theoretically related to another construct's indicators, are observed to be not associated. The most widely used method used to measure discriminant validity is Fornell–Larcker criterion. According to this criterion, for establishing discriminant validity, AVE's square root should be greater than the latent variable correlations [58]. The results revealed that the Fornell–Larcker criterion was satisfied for all the constructs used in this research (Table 5). Furthermore, the latent variable correlations should not be greater than 0.90 [59] to establish discriminant validity. The results show that the highest latent variable correlation value is 0.661 (between hMCI and sMCI), which is significantly below 0.90. Heterotrait–monotrait (HTMT) ratio, another significant measure to evaluate discriminant validity, was also examined. The HTMT ratios for all the constructs should be below the

cutoff value of 0.85 [58] to confirm discriminant validity. From the results shown in Table 6, HTMT ratios were below 0.85 for all the latent variables, further establishing the model’s discriminant validity.

Table 5. Discriminant validity (Fornell–Larcker criterion).

Latent Variable	ATTD	BHVI	cMCI	fMCI	GRNI1	hMCI	PRVR
ATTD	0.933						
BHVI	0.582	0.931					
cMCI	0.276	0.468	0.858				
fMCI	0.402	0.520	0.500	0.864			
GRNI1	0.337	0.462	0.483	0.473	0.868		
hMCI	0.260	0.305	0.440	0.260	0.395	0.924	
PRVR	−0.051	0.017	0.086	0.182	0.069	−0.071	0.852
sMCI	0.247	0.338	0.477	0.275	0.535	0.661	−0.062

Note. Bold diagonals indicate square root of AVE. AVE = average variance extracted; fMCI = functionally motivated consumer innovativeness; hMCI = hedonically motivated consumer innovativeness; cMCI = cognitively motivated consumer innovativeness; sMCI = socially motivated consumer innovativeness; GRNI = green image; PRVR = privacy risk, ATTD = attitude, BHVI = behavioral intention.

Table 6. Discriminant validity (HTMT ratio).

Latent Variable	ATTD	BHVI	cMCI	fMCI	GRNI	hMCI	PRVR
ATTD							
BHVI	0.63						
cMCI	0.316	0.536					
fMCI	0.449	0.584	0.612				
GRNI	0.371	0.509	0.566	0.558			
hMCI	0.283	0.332	0.509	0.305	0.436		
PRVR	0.055	0.039	0.126	0.222	0.082	0.079	
sMCI	0.265	0.366	0.559	0.321	0.592	0.74	0.077

Note. HTMT = heterotrait–monotrait; fMCI = functionally motivated consumer innovativeness; hMCI = hedonically motivated consumer innovativeness; cMCI = cognitively motivated consumer innovativeness; sMCI = socially motivated consumer innovativeness; GRNI = green image; PRVR = privacy risk, ATTD = attitude, BHVI = behavioral intention.

4.3.3. Structural Model Analysis

The measurement model validation was followed by the structural model analysis for testing the hypothesized relationships. The proposed research model has ten constructs and a total of 14 hypothesized relationships to be tested. The R² value or coefficient of determination values for ATT was 0.229 and BHVI was 0.492, indicating adequate predictive accuracy levels. Figure 2 provides the SEM results with the standardized regression weights. Also, Table 7 presents the detailed results from the hypothesis testing. The results supported seven out of the fourteen hypotheses.

Among the motivated consumer innovativeness factors, fMCI ($\beta = 0.311, p < 0.001$) had a significant influence on attitude. Thus, Hypothesis 1a was supported. However, Hypothesis 1b, 1c, and 1d which proposed the effect of hMCI ($\beta = 0.115, p > 0.05$), cMCI ($\beta = 0.002, p > 0.05$) and sMCI ($\beta < 0.001, p > 0.05$) on attitude were not supported. Meanwhile, the motivated consumer innovativeness factors fMCI ($\beta = 0.198, p < 0.01$) and cMCI ($\beta = 0.182, p < 0.01$) were found to have a significant influence on behavioral intention. Thus, Hypotheses 2a and 2c were supported. Whereas Hypotheses 2b and 2d, which proposed the effect of hMCI ($\beta = -0.001, p > 0.05$) and sMCI ($\beta = 0.028, p > 0.05$) on behavioral intention, were not supported.

Table 7. Hypotheses testing.

Hypothesized Relationship	Path Coefficients (β)	T Statistics	p-Value	Hypothesis Result
H _{1a}	fMCI → ATT	4.279 ***	0.000	Supported
H _{1b}	hMCI → ATT	1.588	0.113	Not supported
H _{1c}	cMCI → ATT	0.032	0.974	Not supported
H _{1d}	sMCI → ATT	0.000	1.000	Not supported
H _{2a}	fMCI → BHVI	3.373 **	0.001	Supported
H _{2b}	hMCI → BHVI	-0.019	0.985	Not supported
H _{2c}	cMCI → BHVI	3.064 **	0.002	Supported
H _{2d}	sMCI → BHVI	0.436	0.663	Not supported
H ₃	GRNI → ATT	2.500 *	0.013	Supported
H ₄	GRNI → BHVI	2.398 *	0.017	Supported
H _{5a}	PRFR → ATT	-0.109	0.879	Not supported
H _{5b}	DELVR → ATT	-0.065	0.798	Not supported
H _{5c}	PRVR → ATT	-0.106	0.059	Supported
H ₆	ATT → BHVI	8.064 ***	0.000	Supported

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

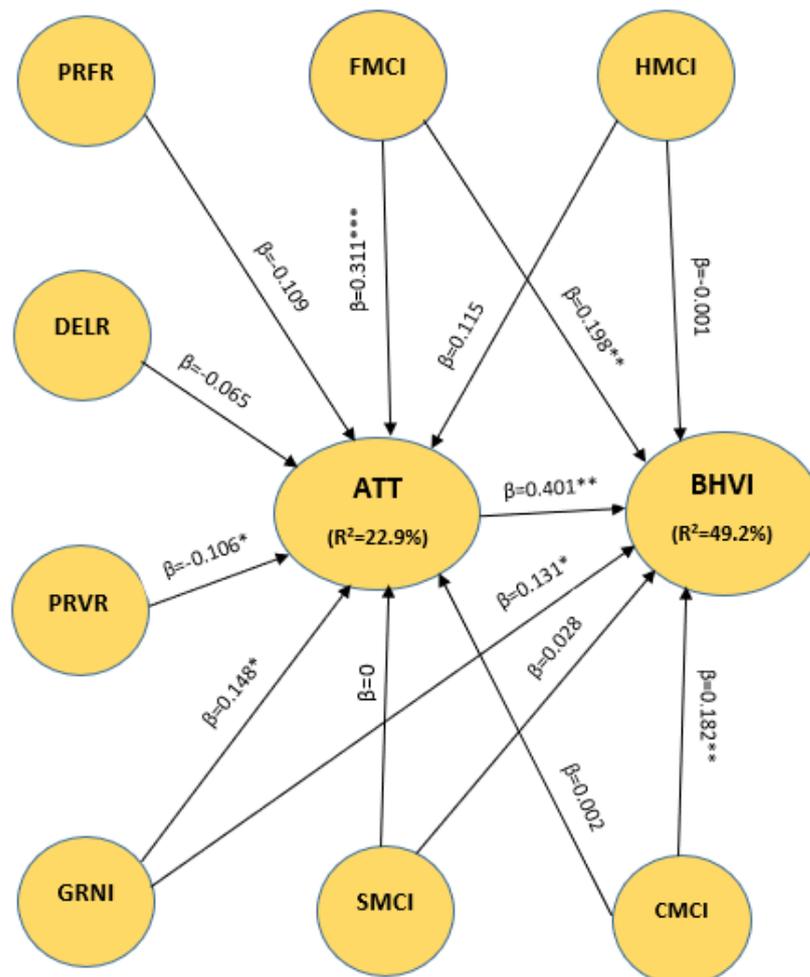


Figure 2. Partial least square results. fMCI = functionally motivated consumer innovativeness; hMCI = hedonically motivated consumer innovativeness; cMCI = cognitively motivated consumer innovativeness; sMCI = socially motivated consumer innovativeness; GRNI = green image; PRFR = performance risk; DLVR = delivery risk; PRVR = privacy risk; ATTD = attitude; BHVI = behavioral intention. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Green image was found to have a significant influence on both attitude ($\beta = 0.131$, $p < 0.05$) and behavioral intention ($\beta = 0.131$, $p < 0.05$). Thus, Hypotheses 3 and 4 were supported. Besides, among the three risk factors considered, privacy risk ($\beta = -0.106$, $p < 0.1$) significantly influenced attitude. However, performance risk ($\beta = -0.109$, $p > 0.05$) and delivery risk ($\beta = -0.065$, $p > 0.05$) were found to have no significant influence on attitude. Therefore, Hypotheses 5c, was supported and Hypotheses 5a and 5b were not supported. Lastly, behavioral intention was significantly influenced by attitude ($\beta = 0.401$, $p < 0.001$), supporting Hypothesis 6.

5. Discussion

This study primarily explores the role of MCI, perceived risk, and green image on consumer attitude and behavioral intentions in the context of drone food delivery services. Evidence from the results indicates that fMCI and cMCI positively and significantly affect both consumer attitude and usage intention while hMCI and sMCI have no significant influence. Research on the influence of consumer innovativeness on drone food deliveries are still in the budding state and mostly conducted in the developed countries. Our findings are in agreement with studies conducted in South Korea and the USA where fMCI and cMCI was found to have a positive influence on behavioral intentions [2,32,38]. However, cMCI did not show any significant relationship [2]. Studies conducted in other contexts of usage of innovative products and services such as robotic restaurants, smart watches, and augmented reality smart glasses etc. seem to be in consensus with the positive impact of functional and cognitive factors for new technology adoption. However, hMCI and sMCI were found to be influencing factors in disagreement with our findings where no influence was recorded [2,61,62]. A possible reason for this seems to be the demographic contrast of the respondents in the two surveys. While the mean age of the former is 35.07 years, 95% of our respondents are between 19–24 years of age, which means they are very much exposed to technology and do not experience much sensory pleasure using a new technology-based product/service. Because of their excessive exposure to technology, the respondents do not find anything new and exciting in an innovative service like drone food delivery. Also, the culture of a nation may play a role in formation of response behavior.

Furthermore, this study investigates the relationship between perceived risks (performance, delivery, and privacy) on attitude and behavioral intention. Like in case of MCI, research related to risk perception of drone deliveries was scarce and mainly carried out in the context of developed nations. The findings of this study showed the negative influence of privacy risk on drone delivery service adoption, while performance and delivery risks did not show significant effects. Similar findings were observed in the US and Korean context [35,52]. However, in the study conducted in Australia, privacy risk was relevant only in the rural setting while performance risk was a concern of the urban public [32]. Though consumers viewed all the three risk factors as influencers, the risks posed by drone usage was stated to be largely comparable with manned aircraft [35]. Consumers may be willing to ignore the occasional malfunctions with drone deliveries because of similar experiences with other technology-based products and services and treat them as initial hiccups that they may consider part of a new technology. Also, in the Indian context, since most of the students do not have their own income, they may be indifferent to occasional losses. However, privacy issues are a matter of great concern for the students as they do not like snooping or cyber surveillance in their private spaces. Yet, it is possible that in acceptance and adoption of certain other innovative products, such as smart glasses, personal privacy did not matter excessively [62].

The results show that the green image of drone food deliveries has a high degree of influence on attitude and behavioral intention. Our findings agree with numerous other studies which indicate that a growing number of people are keen on using environmentally friendly products and services such as drone deliveries, both in developed and developing countries [11,30,46,63,64]. Since the consumers who use the drone delivery services are educated and aware of environmental issues, they are likely to be concerned about reducing

pollution. They will have a positive attitude towards a product/service with a green image and are willing to pay additionally for a green service as demonstrated by numerous studies in other contexts.

6. Conclusions and Implications

Consumers' perception about and reception of an innovative technology depends upon several factors such as MCI, green image, and perceived risk. Each of the four sub-dimensions of MCI—including fMCI, hMCI, cMCI, and sMCI—were analyzed separately. Similarly, three types of risks—namely performance risk, delivery risk, and privacy risk—were considered. The effect of all these constructs directly on attitude and directly or indirectly on behavioral intentions was measured. Out of the four sub-dimensions of MCI, fMCI and cMCI were found to have a significant influence on both attitude and behavioral intentions. It was observed that green image had a significant positive impact on attitude and intentions. However, out of the three sub-dimensions of the perceived risk, only privacy risk was significant. Lastly, as expected, attitude was found to have a significant impact on behavioral intentions.

6.1. Theoretical Implications

This paper is unique in itself because it considers both the driving factors and the impeding factors for the adoption of drone food delivery services. Previous studies have focused on one of these aspects at a time but not all at once.

The Motivated Consumer Innovativeness Scale proposed by Vandecasteele and Geuens, which previously demonstrated high predictive power for innovative buying behavior in the Chinese context, stands valid in the Indian context as well [2,19,20]. Our study's findings imply that the young generation is likely to use this technology not only for convenience, but also out of sheer enthusiasm to enhance their cognitive aptitudes.

Surprisingly, even with a much younger sample age group (19–24 years), the results reveal that privacy risk is considered a significant negative influence for adoption intention. Since most of the respondents are students, it is possible that they are cognizant of the serious data security threats and privacy issues that comes with a new technology like drone food deliveries. Hence, the privacy risk factor needs to be further examined to better understand the effect of age in adopting drone food deliveries. However, delivery and performance risk factors did not seem to have much influence when compared to the privacy risk. This shows that people are not so concerned about the performance and delivery risks associated with this new technology and are willing to accept this innovation's initial hiccups.

This paper is the first to study green image in the Indian context where air pollution is a serious concern; the findings have important theoretical and practical implication due to the unique combination of vast population, size of the service market economy and the demographics of the country. The positive influence of green image on behavioral intentions is encouraging as addressing consumers' environmental needs often translates into usage of eco-friendly services. Drones could potentially play a vital role in reducing environmental implications as they are operated through batteries compared to gasoline-fueled motorbikes extensively used for food deliveries.

Also, since the responses were collected prior to the outbreak of coronavirus, our study can provide a basis to explore the potential change in consumer behavior as users are likely to prefer contactless food delivery practices.

6.2. Managerial Implications

The foodservice industry may want to bolster the functional aspects of drone food delivery, i.e., it should try to make the process more efficient and convenient than conventional means of food delivery such as motorbikes. By focusing on the utilitarian aspects of drone food delivery services, companies can induce motivation among its customers to use it. The food delivery companies must emphasize the functional advantages of drone

deliveries over the conventional modes to its potential customers. Speedy, on-time deliveries are some of the important functional aspects that needs to be highlighted along with pre-ordered deliveries to remote locations inaccessible by motorbikes. The analysis also showed a significant influence of cMCI on behavioral intentions. Foodservice industry may provide new features and various options to satisfy the cognitive desires of the consumer. In addition to marketing strategies that emphasize drone food deliveries' environmental benefits, companies may want to augment the green image by using eco-friendly packaging material. Finally, to counter the significant impact of privacy risk on consumer's attitude, companies need to tighten their cybersecurity norms and ensure protection from data leaks and their misuse or abuse. Consumers' knowledge about drones is still in the early stages. Media, especially social media will play an important role in forming an opinion among users. Food delivery companies must adopt a proactive strategy and act soon to communicate the actual benefits and risks associated, thereby minimizing the possibility of distorted image created via unreliable channels of communication.

Cost savings and environmental benefits can be amplified further with the possibility of large-scale adoption of drone food deliveries. While for unconstrained airspaces, traffic alignment, and segmentation can be employed as mitigation strategies to resolve conflict possibility. Ongoing research studies suggest vertically segmented altitude layers along with horizontal segmentation of drone traffic as one of the effective ways to open constrained urban airspaces for large scale deliveries. High volume drone food deliveries may become a reality with the evaluation of safety, stability, and efficiency factors [65].

The "things" in the internet-of-things are no longer static objects. Innovations—such as drones, autonomous vehicles, etc.—react to context using digital data to interact with other objects, people, and businesses, thereby creating value in the digital economy from information exchange [66]. Drone food deliveries, with the acceptance by its users, will be a part of this digitally connected world.

The government's move to allow commercial use of drones in the country is a welcome step. However, they have an important role in augmenting drone technology to garner industry and public appeal. The drone technology for food delivery is in its nascent stage and would require the government to support entrepreneurs who would like to develop this technology indigenously. This would enable drone delivery services to be offered at affordable prices. Further, the government must formulate stringent policies to protect the consumers from data theft and other privacy-related issues. Lastly, the government should support green technologies such as drone food delivery services by providing adequate subsidies to help this promising technology gain more interest among all the stakeholders.

The development of UAVs for commercial purposes, such as food delivery, would require the collaboration of various technologies. Past studies have reported that UAV supporting technologies such as ground control, flight control, communication technology, signal processing, controller function, and navigation systems are the various channels of open innovation [3], and some of them are interconnected. Therefore, open innovation dynamics become crucial for developing these technologies [67]. Those organizations looking to develop UAV technology for commercial purposes should look for open innovation partners to collaborate and advance the current technology.

7. Limitations and Future Scope

The study's main limitation was that the sample was restricted to college students mostly belonging to the age group of 19–24 years. As youths are primarily tech-savvy, the results cannot be generalized to other consumers, especially the elderly. It would be very beneficial to carry out further work with a larger and diverse demographic sample to have a holistic understanding of customers' attitudes and intentions towards drone food delivery services. Also, the study was conducted in India, where drone delivery services are yet to be commercialized, and people primarily responded to our questionnaire based on their prior knowledge. The attitude and behavioral intentions of respondents could vary in the future after the actual usage. Future studies may explore other factors such as

the cost-effectiveness of drone food deliveries, drone routing issues, job impacts, the effect on traffic congestion, marketing influence, price sensitivity, etc.

This research is the first of its kind in India and one of the very few studies where a comprehensive analysis of consumers' acceptance adoption chances of drone-based food delivery services is attempted. This study comes at a time when the legislation for the commercialization of drones by the foodservice companies is developing rapidly and is therefore valuable to understand the pulse of the people for a future of food deliveries using drones.

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