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Exploring The Enablers Of Passenger Drone Development In India's Aviation Sector: A Factor Analysis And Fuzzy MCDM Approach

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Abstract
Drones have developed quickly and are now used in the logistics, healthcare, military, and agricultural sectors. Their position grew dramatically during the COVID-19 epidemic in several industries, especially transportation, to meet growing client demands and logistical issues. Drones are used for purposes other than delivery, such as emergency medical treatment, precision farming, and surveillance. Emerging industries with enormous economic potential include passenger and package transportation, often known as urban air mobility, where Europe is at the forefront of technology and regulatory developments. This study analyzes public perceptions and expert insights to identify critical enablers for the deployment of passenger drones using exploratory factor analysis (EFA) and fuzzy multi-criteria decision-making (MCDM). The results highlight important elements for successful integration into urban systems, guaranteeing efficiency, safety, and social acceptance.
With an emphasis on factor analysis and fuzzy multi-criteria decision-making (Fuzzy MCDM), this study investigates the factors that facilitate the deployment of passenger drones in India. The coherence of subscales and constructs was evaluated using exploratory factor analysis (EFA), which was validated by Bartlett's test ($p < 0.001$) and KMO (0.691). Eighty-seven percent of the variance was explained by seven factors. Fuzzy MCDM gave expert input ($N=60$) priority to enablers. The findings prioritized infrastructure, innovation, and policy, ranking operational feasibility (0.774), technological advancements (0.758), and regulatory framework (0.735) as key. Safety (0.709) and public acceptance (0.726) were also noteworthy. Although they scored lower, environmental sustainability (0.625) and economic viability (0.696) are nevertheless crucial for long-term adoption. The strategic evolution of passenger drone operations is guided by these findings.
Keywords: *Enablers, Bartlett's test, Exploratory factor analysis, Fuzzy multiple criteria decision making, PCA, Passengers Drones*

1 INTRODUCTION

Drones have found extensive uses in military, SAR (Search and Rescue), agriculture, industry, and logistics, and their capabilities have grown dramatically with the growth of industry (Thibbotuwawa*et al.*, 2020; Rejeb*et al.*, 2021). Most recently, during the global COVID-19 outbreak, drone applications saw a sharp increase (Lin *et al.*, 2022; AlMuhaideb*et al.*, 2021). Large retail chains and package delivery services were forced to look for ways to improve their logistical operations as a result of the COVID-19 restrictive social measures. Customers' expectations for speedy delivery were further raised when a number of internet companies began to provide same-day delivery (Bilinska-Reformat &Dewalska-Opitek, 2021; Raj *et al.*, 2022). For this reason, businesses like FedEx, DHL, and Amazon are attempting to use drones for last-mile delivery (LMD) in order to increase delivery efficiency and speed as well as to make money (Sorooshian*et al.*, 2022; Merkert*et al.*, 2022).

Drones are used in many different industries, such as military, construction, security, health, precision farming, disaster management, humanitarian, and surveillance, and their uses are not just restricted to delivery services (Ayamga*et al.*, 2021). Drones were formerly mostly employed by the military for target killing and tracking enemy movements. These days, they are also employed for image and video mapping, traffic surveillance, and exploring difficult-to-reach places. Drones are used in agriculture to gather real-time data that helps farmers decide how best to modify their inputs in order to increase yields. Drones

are employed in the healthcare industry to swiftly transport emergency medical supplies to far-flung locations, lowering the possibility of problems and fatalities (Li *et al*., 2023).
The use of drones as transport devices for parcel or passenger transport is currently being proposed as a central field for future uses, aside from sensory missions for data collection purposes, such as in construction or agriculture. The European Union is a leader in this field and is working hard to establish itself as a global hub for the development and use of drone services and equipment. The Commission established its activities and institutions in 2013 with the goal of creating a long-term plan for upcoming studies and regulations. The SESAR Joint Undertaking is actively coordinating and focusing research and development to ensure the safe integration of drones into existing airspace in the future, while the European Aviation Safety Agency (EASA) is in charge of developing a unified European regulatory framework for drone use. Europe will soon become "the first region in the world to have a comprehensive set of rules ensuring safe, secure and sustainable operations of drones both, for commercial and leisure activities" following the Commission's adoption of common EU-wide drone regulations in the summer of 2019 (EASA, 2019). The transportation of passengers and packages, which can be summed up with the term "urban air mobility," is a crucial pillar that has the most economic value when it comes to sensory missions and data collecting. According to SESAR, 2018, passenger transport alone is expected to generate a market value of at least EUR 2 billion yearly by 2031, with a market take-off in 2027. More specifically, the three use cases of traveling from the city to the airport, using a cab (far distances), and commuting along congested roads are all included in the estimation of passenger transport in low level airspace. Many nations have built specialized test centers and begun executing national research programs to explore the potential of employing drones as a new mode of transportation (Christen *et al.*, 2018). But in addition to technological and legal considerations, the adoption of drone fleets in the transportation industry will also be greatly influenced by public opinion (Chamata&Winterton, 2018). This is particularly true for urban areas where a significant portion of the populace would be exposed to drones on a regular basis as a result of their introduction into the traffic system. With the use of a qualitative in-depth study, the essay fills this research gap and examines public perceptions of drones as a possible transportation technology against this troubling backdrop.

2 LITERATURE REVIEW

Economic gains account for 49.3% of the expectations surrounding the use of drones for transportation. For a thorough technology assessment, the consequences of technology introduction on the private sector and the macroeconomic environment are extremely important. Therefore, by concentrating on the three benefits specifically connected to transportation—traffic reduction, travel time savings, and environmental relief—we may go on to the benefits that are expected for the (urban) people (20.2%) and the environment (11.3%).
2.1 Ground traffic reduction- Mass motorization has made congestion a major problem, and building road infrastructure frequently results in the ideal of seamless and easy traffic flows (Mom, 2022; Habermas, 1991). However, because of the consequences of induced traffic, initiatives to increase road capacity have failed. Since many physical processes are irreplaceable, the rise of information and communication technologies (ICT) has created hopes that telecommunication will replace physical transportation, but this has shown to be false. Due to its ability to employ distinct air space, drone technology appears to offer a fresh approach to this issue. Although drones can escape traffic jams by raising a portion of ground transportation into the airspace, they are not yet able to perform intricate multiple deliveries. Furthermore, drone deliveries could gain significance if used in conjunction with delivery trucks or in remote humanitarian or individual delivery situations (Delivery,2006; Agatz*et al.*, 2018).
Currently, the only way to significantly reduce land transit is to deploy massive fleets of autonomous drones. The redistribution of traffic flows, however, could result in unforeseen issues and expenses that come with any type of traffic. Additionally, drones could indirectly support the e-commerce industry's upward spiral by enhancing customer satisfaction and lowering delivery costs, which could result in higher traffic flows (Bendel, 2016; Du &Heldeweg, 2017).

Drone flights might be extremely flexible and dense in a well-managed U-Space/UTM, which could help reduce terrestrial traffic even further. On the other hand, overcompensation could result from rebound effects brought on by increased transport sector efficiencies, which would increase both package and passenger transit. Drones may replace ground traffic in this "space-use-dilemma," which is created by the interaction of logistics needs and shifting consumption patterns. However, they also probably produce a new type of (capacious) traffic flow in low-level airspace (Dalkmann, 2007).

2.2 Travel time savings- According to (Banister, 2008), trip times are determined by speed and distance covered, thus drones may save time when compared to ground-based modes of transportation. However, taking into account all technological, procedural, and infrastructure factors is necessary for a thorough evaluation of actual trip time reductions. For expedited transportation, infrastructure elements like drone logistic hubs and public vertiportsare essential (Volocopter, 2019). Door-to-door travel times may increase with lower vertiport densities. Because of their short range and low battery capacity, air taxis are more likely to cut down on journey time in places with poor infrastructure or heavy ground traffic. There are still issues with putting in place the required facilitation systems, particularly in places with limited space. Time reductions in aviation are also hampered by inadequate air traffic control capabilities. Travelers also frequently save time by taking longer or more frequent excursions, which could result in higher traffic volumes and environmental expenses. As a result, the only factors that can be used to assess trip time savings are the density of additional infrastructure, speed, range, and local congestion levels (Balac*et al.*, 2019).

2.3 Sustainable transportation- According to the IPCC, 2014, the transportation industry contributes over 25% of all CO2 emissions worldwide, making it a significant contributor. Land-use policy, technological innovation, and user participation are methods for a sustainable mobility paradigm that aim to create a sustainable future (Banister, 2008). This also applies to drones, which are battery-operated and eco-friendly, preventing pollution in the area. However, in order to measure drone sustainability, a full life cycle study is required.

Drones would need to be entirely fueled by renewable energy sources, have more energy-efficient batteries, and be recyclable or reusable in order to be considered more ecologically friendly. Innovation in technology could make up for drones' energy deficiencies, but it could also have rebound consequences. Energy conservation or sufficiency is required to reduce energy use (Hawkins *et al.*, 2013).

Goodchild & Toy's 2018 (Goodchild & Toy, 2018), reported a recent logistics study has begun comparing the energy efficiency of electric vehicles powered by drones to those powered by traditional fuels. Future research should create a comprehensive evaluation of drones' environmental impacts, including a life cycle analysis of battery-powered drones and comparisons to alternative forms of transportation, as the results of these studies are still incomplete. It's also necessary to weigh the possible savings on current road infrastructure against the impact of additional infrastructure.

2.4 Public Acceptance- The priority that most publications place on the subject of acceptance is what primarily defines it. The majority of scholars looking at the acceptance of commercial drone deployment concur that the populace living in cities will be most affected negatively by the widespread usage of drones (Lidynia*et al.*, 2017). These negative consequences could have a detrimental impact on public acceptance, which is why, after technical and regulatory restrictions, acceptance is listed as one of the three main obstacles to the use of drones for transportation in all publications (15.7%). Nonetheless, it is also feasible to draw attention to potential remedies that attempt to address the issue. Acceptance is mentioned as a prerequisite for drone technology in over one-fifth of the statements found. Nonetheless, 23.9% of the quotations suggest that some usage cases are not accepted. Noise (9%), safety and security (17.9%), and privacy concerns (25.4%) are the primary causes of the lack of acceptability. The goal of most of the suggested fixes is to gain public approval. With an emphasis on laws that protect the public interest, many ideas of sound jurisprudence are thought to be essential for fostering societal acceptability (19.4%). The third-largest category of suggested solutions (14.7%) consists of technical solutions. These include the use of privacy by design techniques (Anbaroglu, 2017) and technical safety precautions (de Miguel&Santamarina, 2018). According to some authors, adding chips to drones would improve accountability (Department for Transport, 2016). Other solutions include developing them in an environmentally sustainable manner and in a more silent manner (Kornatowski*et al.*, 2018). Participatory methods are suggested in an additional 11.7% of all proposals for boosting public approval. Reaching a consensus on (if and) the future use of urban airspace is a specific objective of such public engagement initiatives (Airbus Blueprint,2018).

3 RESEARCH METHODOLOGY

To assess the enablers for passenger drones, this section outlines a methodical approach that combines Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM) and Exploratory Factor Analysis (EFA). Before moving on to the fuzzy MCDM analysis, EFA is used to evaluate the subscale grouping and ensure the formation of coherent factors.

3.1 Sample Size

Sixty experts from a variety of fields, including public policy, environmental sciences, drone technology, urban planning, and aviation, are involved in the project. Following the general guideline that at least 5–10 respondents per variable are necessary for successful factor analysis, the sample size was enough for EFA.

3.2 Data Collection

Using a 5-point Likert scale with linguistic phrases mapped to fuzzy triangular numbers (TFNs), facilitators and their subscales were evaluated. The linguistic terms and their corresponding fuzzy numbers are shown below:

Linguistic Term	Scale Value	Triangular Fuzzy Number (TFN)
Very Low (VL)	1	(0,0,1)
Low (L)	2	(0,1,2)
Moderate (M)	3	(1, 2,3)
High (L)	4	(2,3,4)
Very Low (VH)	5	(3,4,5)

These terms facilitated the transformation of qualitative assessments into quantitative values, making them amenable to fuzzy logic-based analysis (Zahed, 1965; Chen& Hwang, 1992).

3.3 Exploratory Factor Analysis (EFA)

The underlying assumptions for factorability were initially examined to determine whether the dataset was appropriate for exploratory factor analysis (EFA). To ascertain whether the dataset satisfied the requirements for factor analysis, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were specifically performed.

The KMO measure, which provides an index ranging from 0 to 1, was used to assess the sample's appropriateness for factor analysis. Values nearer 1 indicate greater suitability for EFA. To move further with factor analysis, a KMO value of 0.6 or greater was deemed appropriate.

The null hypothesis that the correlation matrix was an identity matrix—which implies that the variables were unrelated and unfit for factor analysis—was examined by Bartlett's Test of Sphericity. There were enough correlations between the variables to move further with EFA, according to a significant result ($p < 0.05$). Therefore, a KMO value of 0.6 or above and a significant result ($p < 0.05$) from Bartlett's Test of Sphericity were necessary for the dataset to be considered suitable for factor analysis (Tabachnick*et al.*, 2013).

3.3.1 Factorability Test

Bartlett's Test of Sphericity

The dataset's factorability was assessed using Bartlett's Test of Sphericity. The existence of linear correlations between the variables is confirmed by this test, which shows that the observed correlation matrix differs statistically from an identity matrix. A result from Bartlett's Test that falls short of the significance level indicates that there aren't enough inter-variable correlations in the dataset to do factor analysis with any degree of accuracy. According to the null hypothesis of Bartlett's Test of Sphericity, the variables are uncorrelated and unfit for factor analysis if the observed correlation matrix equals the identity matrix. The premise that the data are factorable is supported by a significant result ($p < 0.05$), which rejects this null hypothesis and verifies that the correlation matrix differs from an identity matrix sufficiently.

It is recommended to either expand the sample size or eliminate problematic items that contribute to weak or dispersed correlations if the results of Bartlett's Test of Sphericity do not reach statistical significance ($p \geq 0.05$). The factor analysis should be redone after these modifications are made in order to reevaluate the dataset's appropriateness for EFA (Surucu*et al.,* 2022).

Kaiser-Meyer-Olkin Test of Sampling Adequacy

The sample's adequacy for exploratory factor analysis (EFA) was evaluated using the Kaiser-Meyer-Olkin (KMO) Sampling Adequacy Test. The degree of correlation between the variables is shown by the KMO measure, which assesses the percentage of variance in the items that may be common variance. In general, factor analysis can be carried out if the KMO value is more than 0.6, which indicates that the sample size is sufficient to identify underlying components. The sample is not appropriate for factor analysis if the KMO value is less than this cutoff, and changes, like expanding the sample size, might be required (Surucu*et al.,* 2022).

3.4 Factor Extraction

To lower the dimensionality of the data, the first extraction technique was Principal Component Analysis (PCA). The factor loadings were obtained by performing a second factor analysis once the number of factors was established.

3.5 Rotation Method

Varimax rotation (orthogonal) is applied to improve interpretability. Varimax rotation, an orthogonal rotation technique, was used to increase the extracted factors' interpretability. By maximizing the variance of factor loadings and making sure that each variable loads heavily on one factor and little on others, varimax rotation streamlines the factor structure. When the underlying dimensions are regarded as independent, this method works well since it assumes that the factors are uncorrelated. The factors were then interpreted and labeled using the rotated factor matrix, which displays more pronounced and identifiable loading patterns.

3.6 Factor Loading

Subscales in this study were deemed significant contributors to their respective factors if their factor loadings were higher than 0.5. A moderate to strong association between the variable and the factor is indicated by a factor loading greater than 0.5, which implies that the variable is a significant reflection of the underlying concept. Variables with loadings below this cutoff were eliminated from the final factor interpretation since they were deemed to be weaker contributors. By ensuring that each component is defined using just the most pertinent variables, this criterion contributes to the factor structure's increased validity and clarity (Hair *et al.,* 2019).

3.7 Criteria for proceeding to Fuzzy Analysis

Each scale's subscales were put together according to their factor loadings to create unique, interpretable factors. Scales were supposed to be easily distinguished and make a significant contribution to the overall factor structure, with each component representing a logical, independent dimension. Subscales that lacked a clear relationship with one of the factors were not included in the analysis.

3.8 Fuzzy MCDM Analysis

The priority problem was addressed using fuzzy multi-criteria decision-making (MCDM) analysis following EFA validation of the scales and subscales. Finding and classifying the enablers was the first step in defining the problem structure. By comparing enabler pairs using a language scale, which was subsequently translated into triangular fuzzy numbers to measure the effect strength and account for uncertainty, a study of their mutual influence was carried out. This method allowed for a more accurate and adaptable prioritization procedure.

3.8.1 Fuzzy Membership Function Assignment

To reflect the group's overall opinion, the experts' assessments of the subscales' relative relevance were combined into Triangular Fuzzy Numbers (TFNs). TFNs express the range of potential outcomes using three values, which captures the uncertainty in expert opinions.
The aggregated fuzzy number for each subscale was computed using the formula (Equation 1):

$$\tilde{A}_{subscale} = \frac{1}{N}\sum_{i=1}^{N}\tilde{A}_i$$

Where:
$\tilde{A}_i$ = represents the TFN assigned by the i^{th} expert.
N = 60, the number of experts.
This aggregation ensured a consensus-based representation of expert opinions while retaining the imprecision inherent in individual responses [38].

3.8.2 Aggregation at the Scale Level

Each of the seven scales (e.g., Regulatory Framework, Technological Advancements) was evaluated by averaging the aggregated fuzzy values of its corresponding subscales. In order to get a single fuzzy value that represented the collective judgment for that scale, this procedure entailed averaging the Triangular Fuzzy Numbers (TFNs) for each subscale inside a scale. Based on the combined expert ratings, the scales were then prioritized and their relative importance was evaluated using the averaged fuzzy values (Equation 2) (Zimmermann, 2011).

$$\tilde{A}_{scale} = \frac{1}{k}\sum_{j=1}^{k}\tilde{A}_{subscale\ j}$$

Where:
k is the number of subscales in a scale.
$\tilde{A}_{subscale\ j}$ represents the aggregated fuzzy value of the j^{th} subscale.
This step produced a single aggregated fuzzy value for each scale, simplifying further analysis.

3.8.3 Defuzzification

The weighted average approach of defuzzification was used to transform the total Triangular Fuzzy Numbers (TFNs) into distinct values. By taking the weighted average of the lower, middle, and upper values of the triangle fuzzy numbers according to their relative importance or frequency, this method produces a single, distinct value. The precise prioritizing of the scales and subscales is represented by the defuzzified crisp values, which preserve the uncertainty and variability contained in the expert evaluations while facilitating clearer decision-making (Chen, 1996; Chen & Hwang, 1992).
The formula used was (Equation 3):

$$Crisp\ Value = \frac{(a + 4b + c)}{6}$$

Where: a, b, and c represent the lower, middle, and upper bounds of the triangular fuzzy number, respectively.
This formula balances the influence of the most likely value (b) and the range of possible values (a and c), providing a robust measure of central tendency.

3.8.4 Ranking of Scales

The elements were clearly prioritized by ranking the enablers using the defuzzified crisp values for each scale. The most important facilitators for the development of passenger drones were highlighted by this ranking, which made it possible to compare the relative significance of each scale. The analysis's identification of the crucial parts allowed for focused decision-making, guaranteeing that the most important aspects were prioritized in the creation and application of passenger drone technology.

3.8.5 Ranking Formula

The scales' defuzzed, crisp values were arranged in descending order. The most significant scales were found by this ranking method, where higher, more distinct values denoted greater significance. The research produced a clear hierarchy of enablers by sorting the scales from highest to lowest, indicating

which elements are most important for the development of passenger drones and ought to receive priority in further initiatives.
Rank = Order of Crisp Values (C)
This ranking process helped prioritize efforts and resources for enhancing the identified enablers.

4 Data Analysis

4.1 Factor Analysis

Exploratory Factor Analysis (EFA) was used to begin the data analysis in order to accomplish two main goals. Its primary goal was to determine whether the subscales inside each scale were arranged logically and cogently, reflecting the scales' fundamental structure. In order to ensure that the constructs being assessed could be clearly distinguished from one another, it also aimed to ascertain whether each scale comprised a unique factor or component.

4.2 Analysis and Interpretation

The statistical method used to evaluate the sample's sufficiency is the Kaiser-Meyer-Olkin (KMO) test. This evaluation determines whether the data is sufficient for factor analysis and whether the sample is appropriate for each individual variable and the model as a whole. To guarantee the sample's sufficiency, the KMO test value must be higher than 0.5 (Kaiser, 1974). To determine whether multicollinearity exists among the variables used in component analysis, the Bartlett's test of sphericity is used (Bartlet, 1950).
The sample is sufficient for the factor analysis, according to the KMO test value of 0.691 (>0.5), and the Bartlett's test of sphericity shows that there is no multicollinearity among the variables, with a significant p-value of 0.000 (<0.001) and an approximate chi-square value of 2101.843 with a degree of freedom of 435.
Seven components out of thirty variables are retrieved using Principal Component Analysis in accordance with proposal (Kaiser, 1960). These factors account for 87.132 percent of the variability.

Table 1 Extracted factors with their Eigenvalues, % of Variance and cumulative
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.074	30.247	30.247	9.074	30.247	30.247	4.390	14.633	14.633
2	4.392	14.639	44.886	4.392	14.639	44.886	4.039	13.464	28.097
3	3.563	11.876	56.762	3.563	11.876	56.762	3.673	12.242	40.339
4	3.066	10.219	66.981	3.066	10.219	66.981	3.663	12.210	52.550
5	2.424	8.080	75.061	2.424	8.080	75.061	3.545	11.815	64.365
6	1.911	6.369	81.430	1.911	6.369	81.430	3.493	11.642	76.007
7	1.711	5.702	87.132	1.711	5.702	87.132	3.338	11.125	87.132

The straightforward connections between variables and factors are referred to as factor loadings. The degree to which the items may accurately reflect the underlying component was shown by factor loadings. The factor loadings of every variable on every extracted factor were included in the factor matrix. Principal components extraction and factor analysis were used in the study to determine whether they reflect distinguishable components connected to variables affecting user willingness and demand. The loadings of the different factors are shown in the table below.

Table 2 Loadings of factor by Rotational Component Matrix
Rotated Component Matrix

Latent variable Name		Variable	Loading
Regulatory Framework	←	Regu_1	0.941

	←	Regu_5	0.898
	←	Regu_2	0.892
	←	Regu_3	0.878
	←	Regu_4	0.860
Operational Feasibility	←	Opera_1	0.950
	←	Opera_2	0.895
	←	Opera_4	0.852
	←	Opera_5	0.838
	←	Opera_3	0.828
Environmental Sustainability	←	Environ_1	0.965
	←	Environ_3	0.920
	←	Environ_2	0.907
	←	Environ_4	0.898
Economic Viability	←	Economic_1	0.917
	←	Economic_2	0.902
	←	Economic_3	0.897
	←	Economic_4	0.895
Public Acceptance	←	Accep_1	0.906
	←	Accep_4	0.879
	←	Accep_2	0.860
	←	Accep_3	0.845
Safety and Security	←	Safety_1	0.915
	←	Safety_2	0.894
	←	Safety_4	0.888
	←	Safety_3	0.825
Technological Advancements	←	Techno_1	0.958
	←	Techno_2	0.870
	←	Techno_4	0.856
	←	Techno_3	0.841

All of the subscales within each scale were put together in a logical and consistent manner, according to the results of the Exploratory Factor Analysis (EFA). Additionally, each scale clearly loaded into distinct variables, allowing the constructions to be clearly distinguished from one another. These results guarantee the validity and reliability of ensuing assessments by validating the underlying measurement framework and offering a strong basis for moving further with the Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM) study.

4.3 Fuzzy MCDM

The EFA results showed considerable distinction between constructs and coherence among subscales, offering a strong basis for additional investigation. Building on these findings, Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM) was applied to prioritize the identified enablers systematically, considering the inherent uncertainties and complexities of decision-making in this new industry. This method guarantees a thorough assessment of the elements essential to developing passenger drone operations in the Indian setting.

The steps of the Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM) process were outlined as follows:

4.4 Definition of Linguistic Terms and Fuzzy Numbers

Linguistic phrases like "Very Low," "Low," "Moderate," "High," and "Very High" were mapped to equivalent Triangular Fuzzy Numbers (TFNs) in order to statistically reflect qualitative judgments. These terms were given numerical ranges by the mapping as follows: Very Low (VL): (0, 0, 1), Low (L): (0, 1, 2), Moderate (M): (1, 2, 3), High (H): (2, 3, 4), and Very High (VH): (3, 4, 5). This mapping allows subjective expert assessments to be mathematically represented while taking into account the ambiguity and uncertainty that comes with linguistic evaluations.
These fuzzy numbers take into account the inherent ambiguity in language assessments and make it easier to mathematically treat subjective expert evaluations.

4.5 Collection of Expert Responses

To assess each subscale of the enablers found in the study, 60 domain experts were asked for their expert judgments. For instance, expert responses were dispersed among the subscales of the Regulatory Framework scale as follows:

Table 3 Expert response for Regulatory Framework

Scales	Subscales	VL	L	M	H	VH
1. Regulatory Framework	Well-defined policies and regulations for passenger drones.	5	5	8	23	19
	Simplified licensing processes.	4	3	11	18	24
	Government support through subsidies or incentives.	4	5	7	17	27
	Legal complications and protocols associated with passenger drones.	3	3	14	16	24
	Compliance with international aviation safety standards.	2	5	11	17	25

To fully collect data for the ensuing study, same procedure was done for each of the other scales that were found. These actions set the stage for employing fuzzy MCDM to prioritize the enablers for passenger drones in the Indian aviation industry.

4.6 Aggregate Expert Responses into Fuzzy Numbers

The answers from 60 experts were combined to create Triangular Fuzzy Numbers (TFNs) for each subscale. Each linguistic term's TFNs are weighted according to the percentage of experts that selected it as part of the aggregation procedure. This aggregate is calculated using the following formula:

$$\tilde{A}_{subscale} = \frac{1}{N}\sum_{i=1}^{N}\tilde{A}_i$$

Where: $\tilde{A}_i$ = represents the TFN assigned by the i^{th} expert.
N = 60, the number of experts.
This aggregation ensured a consensus-based representation of expert opinions while retaining the imprecision inherent in individual responses.
Well-defined policies and regulations

Table 4 Aggregate TFN for well defined policies and regulations

Term	TFN	Number of Experts	Contribution to Aggregated TFN
VL	(0,0,1)	5	$^5/_{60}$ X $(0,0,1)$ = (0,0,0.083)
L	(0,1,2)	5	$^5/_{60}$ X $(0,1,2)$ = (0,0.083,0.167)
M	(1,2,3)	8	$^8/_{60}$ X $(1,2,3)$ = (0.133,0.267,0.4)
H	(2,3,4)	23	$^{23}/_{60}$ X $(2,3,4)$ = (0.767,1.15,1.533)
VH	(3,4,5)	19	$^{19}/_{60}$ X $(3,4,5)$ = (0.95,1.267,1.5833)

Aggregated TFN for "Well-defined policies and regulations":
$\tilde{A}$ = (0,0,0.083) + (0,0.083,0.167) + (0.133,0.267,0.4) + (0.767,1.15,1.533) + (0.95,1.267,1.5833) = (1.85, 2.767, 3.767)
Repeat the same process for the other subscales.

Normalize the Aggregated TFNs
The aggregated TFNs were normalized by dividing each TFN by the highest upper limit across all subscales in order to guarantee comparability between subscales. The maximum upper limit for the Regulatory Framework scale was 3.967.
Normalization formula: $\tilde{A}_{scale} = \frac{\tilde{A}}{\max(\tilde{A})}$

The aggregated TFNs for the five subscales of Regulatory Framework are
Table 5 Normalized TFN for Regulatory Framework

Subscales of Regulatory Framework	Aggregated TFN	Normalized TFN
Well-defined policies and regulations for passenger drones.	(1.85, 2.767, 3.767)	(0.466, 0.697, 0.949)
Simplified licensing processes.	(1.983, 2.917, 3.917)	(0.5, 0.735, 0.987)
Government support through subsidies or incentives.	2.033, 2.967, 3.967)	(0.513, 0.748, 1)
Legal complications and protocols associated with passenger drones.	(1.967, 2.917, 3.917)	(0.496, 0.735, 0.987)
Compliance with international aviation safety standards.	(2, 2.967, 3.967)	(0.504, 0.748, 1)

4.7 Aggregation at the Scale Level
To evaluate the overall aggregated fuzzy number for each scale, the normalized TFNs of its subscales were averaged:

$$\tilde{A}_{scale} = \frac{1}{k}\sum_{j=1}^{k} \tilde{A}_{subscale\ j}$$

Where:
k is the number of subscales in a scale.
$\tilde{A}_{subscale\ j}$ represents the aggregated fuzzy value of the j[th] subscale.
This step produced a single aggregated fuzzy value for each scale, simplifying further analysis. For Regulatory Framework, the aggregated fuzzy value is given below:

$$\tilde{A}_{RF} = {}^{1}/_{5}\big((0.466, 0.697, 0.949) + (0.5, 0.735, 0.987) + (0.513, 0.748, 1) + (0.496, 0.735, 0.987) + (0.504, 0.748, 1)\big) = (0.496, 0.733, 0.985)$$

The aggregated TFN of the 7 Scales are calculated.
4.8 Defuzzification and Ranking
To rank the scales, the aggregated fuzzy numbers were defuzzified into crisp values using the weighted average method:

$$Crisp\ Value = \frac{(a + 4b + c)}{6}$$

Where a, b, and c represent the lower, middle, and upper bounds of the triangular fuzzy number, respectively.
The enablers were ranked using the defuzzed crisp values on each scale. The ranking revealed the most crucial elements for the development of passenger drones and shed light on the relative significance of the scales.
Table 6 Ranking of Enablers

Scales	Aggregated TFN	Crisp Value	Rank
Regulatory Framework	(0.496, 0.733, 0.985)	0.735	3
Technological Advancements	(0.525, 0.757, 0.994)	0.758	2
Economic Viability	(0.437, 0.690, 0.979)	0.696	6
Public Acceptance	(0.474, 0.721, 0.995)	0.726	4

Operational Feasibility	(0.556, 0.774, 0.993)	0.774	1
Environmental Sustainability	(0.334, 0.610, 0.976)	0.625	7
Safety and Security	(0.454, 0.705, 0.981)	0.709	5

5 RESULTS

5.1 Operational Feasibility (Crisp Value: 0.774, Rank: 1)

The top objective was operational viability, highlighting how crucial it is to establish a strong basis for passenger drone operations. This entails establishing the required infrastructure (such as vertiports) and making certain that air traffic control systems can integrate drones. Additionally, important are investments in safety procedures and staff development (trained operators and technicians).

5.2 Technological Advancements (Crisp Value: 0.758, Rank: 2)

Second place went to technological developments, highlighting the necessity of ongoing innovation. The development of safe communication networks, increased drone autonomy, and improved battery efficiency should be the main priorities. Additionally, in order to accommodate drones in urban settings, UAM infrastructure development is essential.

5.3 Regulatory Framework (Crisp Value: 0.735, Rank: 3)

Establishing precise rules and guaranteeing the security and incorporation of passenger drones into the aviation sector requires a strong regulatory framework. To promote industry growth, policymakers should concentrate on creating thorough regulations, streamlining licensing procedures, and offering incentives.

5.4 Public Acceptance (Crisp Value: 0.726, Rank: 4)

Public acceptance became a top priority, highlighting the necessity of programs aimed at fostering trust. Increased acceptability can be facilitated by public education and outreach initiatives that highlight safety, environmental issues, and the advantages of passenger drones. For broader public support, it will also be crucial to address concerns like privacy and noise.

5.5 Safety and Security (Crisp Value: 0.709, Rank: 5)

The public's concern for passenger safety and operational dependability was demonstrated by the high rankings given to safety and security. Gaining trust and guaranteeing the seamless operation of passenger drones requires a strong emphasis on safety procedures, such as real-time monitoring and assessments in a variety of weather situations.

5.6 Economic Viability (Crisp Value: 0.696, Rank: 6)

A key component of passenger drones' long-term sustainability is their economic feasibility. Cost-effective technology and business strategies that make drone services accessible to the general population are required to promote investment and adoption. In order to make drones a financially feasible substitute for conventional modes of transportation, both the public and commercial sectors must invest in scalable manufacturing and operational models.

5.7 Environmental Sustainability (Crisp Value: 0.625, Rank: 7)

Environmental sustainability is still a significant factor, even though it came in lower than other aspects. Passenger drones must have as little of an environmental impact as possible, with an emphasis on lowering noise and emissions, in order to meet global sustainability targets. Drone operations can also become more environmentally friendly by utilizing renewable energy sources.

6 CONCLUSION

All of the subscales within each scale were put together in a logical and consistent manner, according to the results of the Exploratory Factor Analysis (EFA). Additionally, each scale clearly loaded into distinct variables, allowing the constructions to be clearly distinguished from one another. These results guarantee the validity and reliability of ensuing assessments by validating the underlying measurement framework and offering a strong basis for moving further with the Fuzzy Multi-Criteria Decision-Making (Fuzzy MCDM) study.

Key findings from the Fuzzy MCDM analysis were as follows:

The top three criteria were found to be operational feasibility, technological advancements, and regulatory framework, suggesting that these factors are crucial for facilitating the deployment of passenger drones.

- The significance of establishing societal trust and guaranteeing operational safety was reflected in the rigorous follow-up of Public Acceptance and Safety and Security.
- Although it was ranked somewhat lower, economic viability was recognized as a crucial facilitator, highlighting the necessity of affordable solutions to guarantee widespread market adoption.
- Environmental sustainability, which focuses on lessening the ecological impact of drone activities, was regarded as a secondary consideration despite its importance.

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